Security Analysis: An Investment Perspective

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Abstract

The investment CAPM, in which expected returns vary cross-sectionally with investment, profitability, and expected growth, provides an economics-based, conceptual foundation for Graham and Dodd (1934). The q^5 model goes a long way in explaining prominent security analysis strategies, such as Frankel and Lee's (1998) intrinsic-to-market value, Piotroski's (2000) fundamental score, Greenblatt's (2005) "magic formula," Asness, Frazzini, and Pedersen's (2019) quality-minus-junk, Bartram and Grinblatt's (2018) agnostic analysis, Penman and Zhu's (2014, 2018) fundamental strategies, and Ball, Gerakos, Linnainmaa, and Nikolaev's (2020) retained earnings-to-market, as well as best-performing active, discretionary value funds, such as Buffett's Berkshire.

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1 Introduction

Graham and Dodd (1934, 1940, *Security Analysis*) pioneer an investment philosophy that buys undervalued securities selling below their intrinsic values. Their teachings have had a long-lasting impact on the investment management industry. Many famous investors such as Warren Buffett, Joel Greenblatt, and Charlie Munger follow the Graham-Dodd philosophy. The publication of their 1934 magnus opus has also helped create the financial analysts profession. Alas, perhaps because it is premised on the discrepancy between the intrinsic value and the market value of a security, security analysis has long been perceived as incompatible with modern finance, the bulk of which builds on efficient markets (Fama 1965, 1970). This perspective pervades the contemporary literature in finance and accounting (Bartram and Grinblatt 2018; Asness, Frazzini, and Pedersen 2019; Sloan 2019).

Our insight is that the investment-based capital asset pricing model (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). A restatement of the net present value rule in corporate finance, the investment CAPM says that a firm's discount rate equals the incremental benefit of the marginal project divided by its incremental cost. The incremental benefit can be gauged with quality metrics, such as profitability and expected growth, whereas the incremental cost is closely tied to Tobin's q. As such, to earn high expected returns, the theory says that investors should buy high quality stocks at bargain prices, a prescription that is exactly what Graham and Dodd have been saying and equity analysts have been practicing for 85 years.

As the theory's empirical implementation, we show that the q^5 model largely explains prominent security analysis strategies, including Frankel and Lee's (1998) intrinsic-to-market value, Piotroski's (2000) fundamental score, Greenblatt's (2005) "magic formula," Asness, Frazzini, and Pedersen's (2019) quality-minus-junk, Bartram and Grinblatt's (2018) agnostic fundamental analysis, Penman and Zhu's (2014, 2018) expected return strategies, and Ball, Gerakos, Linnainmaa, and Nikolaev's

(2020) retained earnings-to-market. These quantitative strategies are mostly different combinations of investment, profitability, and expected growth, which are the key expected return drivers in the investment CAPM. Perhaps more important, for active, discretionary value funds that might not follow rule-based, quantitative strategies, we show that the q^5 model also goes a long way in explaining their performance. The investment and return on equity factors help explain Buffett's Berkshire, and the investment factor plays a leading role in explaining other best-performing active funds.

The investment factor largely accounts for Frankel and Lee's (1998) intrinsic-to-market anomaly. The key driving force is the investment-value linkage in the investment CAPM, which 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. In the 1967–2018 sample, the high-minus-low intrinsic-to-market quintile earns on average 0.27%, 0.35%, and 0.36% per month ($t = 2.01$, 2.25, and 2.29) across micro, small, and big stocks, and the q^5 alphas are 0.13%, 0.13%, and 0.11% ($t = 1.05$, 0.88, and 0.68), helped by the large investment factor loadings of 0.5, 0.7, and 0.72 ($t = 4.8$, 5.38, and 5.77), respectively.

Piotroski's (2000) fundamental score combines 9 signals on profitability, liquidity, and operating efficiency. The return on equity (Roe) factor largely accounts for this accounting anomaly. The high-minus-low quintile earns 0.5%, 0.36%, and 0.28% per month ($t = 3.25$, 2.5, and 1.78) across micro, small, and big stocks, and the q^5 alphas are 0.33%, 0.1%, and 0.03% ($t = 2.67$, 0.81, and 0.15), helped by the large Roe factor loadings of 0.59, 0.45, and 0.39 ($t = 6.12$, 5.49, and 3.77), respectively.

Greenblatt (2005, 2010) proposes a "magic formula" that buys good companies (high returns on capital) at bargain prices (high earnings yield). The Roe factor is the key driving force underlying his formula, with the investment and expected growth factors playing a secondary role. The high-minus-low quintile earns 0.43%, 0.47%, and 0.47% per month ($t = 2.51$, 2.87, and 3.08) across micro, small, and big stocks, and the q^5 alphas are 0.06%, 0.03%, and −0.11% ($t = 0.43$, 0.18, and −0.84), helped by the large Roe factor loadings of 0.67, 0.57, and 0.39 ($t = 6.1$, 5.08, and 4.51), respectively.

Asness, Frazzini, and Pedersen (2019) measure quality as a combination of profitability, growth, and safety, for which investors are willing to pay a high price. In our sample, the quality-minus-junk quintile earns on average 0.61%, 0.42%, and 0.22% per month ($t = 3.92$, 3.19, and 1.53) across micro, small, and big stocks, with the q^5 alphas of 0.3%, 0.09%, and 0.07% ($t = 2.45$, 0.83, and 0.59), respectively. High quality stocks 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 strong 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 0.92%, 0.5%, and 0.46% per month ($t = 4.25$, 2.42, and 2.11) across micro, small, and big stocks, but the q^5 model reduces the return spreads to insignificance, with alphas of 0.48%, 0.27%, and 0.42% ($t = 1.82$, 1.23, and 1.7), respectively. The investment factor again plays a key role in driving the model's performance.

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

Ball, Gerakos, Linnainmaa, and Nikolaev (2020) show that retained earnings-to-market forecasts returns reliably and subsumes the book-to-market premium. The high-minus-low quintile earns on average 0.57%, 0.44%, and 0.43% per month ($t = 2.81$, 2.3, and 2.38) across micro, small, and big stocks, and the q^5 model reduces the return spreads to insignificance, with alphas of 0.1%, -0.06%, and -0.28% ($t = 0.63, -0.42$, and -1.7), respectively. Arising again from the investment-value linkage, the investment factor loadings are economically large and highly significant.

The q and q^5 models also go a long way in explaining best-performing active, discretionary value funds, which exploit hard-to-quantify, qualitative information. In the February 1968–December 2018 sample, Warren Buffett's Berkshire Hathaway earns 1.44% per month ($t = 4.96$) in excess of the riskfree rate. The q-factor model reduces the return spread by 56% to an alpha of 0.64%, albeit still significant ($t = 2.45$), and the q^5 model yields an alpha of 0.77% ($t = 2.69$). More generally, the aggregate equal- and total net assets-weighted portfolios of active value funds in the CRSP Mutual Fund database barely beat the market portfolio and underperform the q and q^5 models by 8–11 basis points per month. Most important, for portfolios that consist of *only* top-20 active value funds, the q^5 model explains 69–89% of their performance, depending on specific measurement.

Our work reconciles Graham and Dodd's (1934) security analysis with Fama's (1970) efficient markets. On the one hand, Graham and Dodd implicitly assume a constant discount rate and attribute return predictability with accounting variables to mispricing. In contrast, the investment CAPM features cross-sectionally varying expected returns, depending on investment, profitability, and expected growth. By connecting expected returns to accounting variables, but without expectation errors, we show that security analysis *should* work within efficient markets to begin with.

On the other hand, academic finance, with the Sharpe (1964) and Lintner (1965) CAPM as the workhorse theory, dismisses security analysis profits as due to luck and recommends investors to hold only the market portfolio (Bodie, Kane, and Marcus 2017). Instead of the first principle of investors, we pin down expected returns via the first principle of security issuers. By inheriting Graham and Dodd's (1934) primary focus on firms, we validate security analysis on equilibrium grounds and pinpoint key expected return drivers, including investment, profitability, and expected growth.

To our knowledge, Ball (1978) is the first to argue that accounting information is connected with expected returns, especially when scaled by price. Intuitively, price is a function of expected dividends and expected returns. It follows that 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. As such, scaled by price, earnings reveals information about expected returns. Berk (1995) echoes some of these insights in the context of the size anomaly. Ball and Brown (1968) and Ball, Gerakos, Linnainmaa, and Nikolaev (2015, 2016, 2020) test these insights with different measures of earnings yields. We show, conceptually, how the investment CAPM provides a microeconomic foundation for the linkages between accounting information and expected returns; and, empirically, how the q^5 model adequately accounts for security analysis strategies in detail.

Our perspective on security analysis echoes Penman and Zhu (2014), who write that "the returns to anomaly variables are consistent with rational pricing in the sense that the returns are those one would expect if the market were efficient in its pricing (p. 1836)." Penman and Zhu use clean surplus relation to rewrite expected returns as the sum of expected earnings yield and the expected change in the market equity's deviation from the book equity. The latter component can be linked to expected earnings growth (as well as risk and expected returns) via poweful accounting insights (Penman, Reggiani, Richardson, and Tuna 2018).[1] For comparison, the tight, economic linkage between investment and the market equity allows us to substitute, mathematically, expected capital gain with expected investment growth. As such, the investment CAPM is perhaps even more "fundamental" than the Penman-Zhu model, which still has the market equity in its formulation.

Hou, Xue, and Zhang (2015) implement the investment CAPM with the q-factor model, and Hou, Mo, Xue, and Zhang (2020) add expected growth to form the q^5 model. We differ in two ways. Conceptually, we are the first to show how financial statement analysis originated from Graham and Dodd (1934) can be reconciled with modern finance via cross-sectionally varying expected returns.

[1]For example, in Penman and Reggiani (2013), the deferral of earnings recognition raises expected earnings growth, which might deviate from subsequent realized earnings growth. This risk might be embedded in expected returns. Penman and Zhu (2018) emphasize that intangible assets are not booked when earnings from investments such as research and development and advertising are uncertain. These investments are expensed against earnings, reducing current earnings but inducing higher expected earnings growth, which is risky because of the uncertainty.

Empirically, we document new, extensive evidence that the q^5 model goes a long way in explaining prominent security analysis strategies, their interactions with size, and more important, active, discretionary value funds. However, as in our prior work, we emphasize that our evidence does not rule out distorted beliefs on the investor side. Rather, overturning the conventional wisdom that security analysis suggests only mispricing, we show that security analysis should work in efficient markets.

The rest of the paper unfolds as follows. We describe traditional views on security analysis and offer our new, economics-based perspective in Section 2. We use the q^5 model to explain quantitative strategies rooted in security analysis in Section 3 and active value funds in Section 4. We conclude in Section 5. A separate Internet Appendix details measurement and supplementary results.

2 An Economics-based Perspective on Security Analysis

Section 2.1 reviews the original Graham-Dodd perspective. Section 2.2 presents traditional, conflicting academic views in finance and accounting. Finally, Section 2.3 offers our new, 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)."[2] The basic philosophy is to invest in undervalued securities that are selling well below the intrinsic value, which is "that value which is justified by the facts, e.g., the assets, earnings, dividends, definite prospects, as distinct, let us say, from market quotations established by artificial manipulation or distorted by psychological excesses (p. 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

[2]Our references to specific page numbers are from Graham and Dodd (1940), the classic second edition, which is generally viewed as more authoritative, see, for example, https://www.youtube.com/watch?v=AZFFKF30Y9I.

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 finance and accounting literature offers contradicting perspectives on security analysis. On the one hand, the fundamental analysis literature in accounting, launched by Ou and Penman (1989), has largely subscribed to the Graham-Dodd perspective: "Rather than taking prices as value benchmarks, 'intrinsic values' discovered from financial statements serve as benchmarks with which prices are compared to identify overpriced and underpriced stocks. Because deviant prices ultimately gravitate to the fundamentals, investment strategies which produce 'abnormal returns' can be discovered by the comparison of prices to these fundamental values (p. 296)."

Bartram and Grinblatt (2018) start with the basic premise: "A cornerstone of market efficiency is the principle that trading strategies derived from public information should not work (p. 126)." "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) writes: "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. For example, Fama (1965) writes: "If the random walk theory is valid and if security exchanges are 'efficient' markets, then stock prices at any point in time will represent good estimates of intrinsic or fundamental values. Thus, additional fundamental analysis is of value only when the analyst has new information which was not fully considered in forming current market prices, or has new insights concerning the effects of generally available information which are not already implicit in current prices. If the analyst has neither better insights nor new information, he may as well forget about fundamental analysis and choose securities by some random selection procedure (p. 59)."

This perspective has mostly persisted today. In a leading textbook on investments, Bodie, Kane, and Marcus (2017) write: "[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. 356, original emphasis)." In a Bloomberg interview on November 5, 2019, Fama even labels equity research on Wall Street as "business-related pornography."[3]

2.3 Our New, Economics-based Perspective

Realized returns equal expected returns plus abnormal returns. Tautologically, predictability with any anomaly variables, including those arising from security analysis, has two parallel interpreta-

[3]https://www.bloomberg.com/news/videos/2019-11-08/bloomberg-opinion-masters-in-business-eugene-fama-and-david-booth-11-05-2019-video

tions. In the first interpretation, the variables forecast abnormal returns, meaning that forecasting errors are forecastable, violating efficient markets, as in Graham and Dodd (1934, 1940).[4] In the second interpretation, the anomaly variables are connected, cross-sectionally, to expected returns. However, abnormal returns are unpredictable, thereby retaining efficient markets (Zhang 2017).

2.3.1 An Equilibrium Model of Security Analysis Based on 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.[5] The right-hand side is the marginal benefit of investment at time $t+1$ over the marginal cost of investment at t. In the numerator, X_{t+1} is the marginal profit, $(a/2)(I_{t+1}/A_{t+1})^2$ the marginal reduction in adjustment costs, and the last term the marginal continuation value of the extra unit of assets net of depreciation.

For quantities, equation (1) formalizes the net present value rule of capital budgeting in corporate finance. Intuitively, the equation says that a firm should keep investing until the marginal cost of investment, which rises with investment, equals the present value of additional investment, which is the next period marginal benefit of investment discounted by the cost of capital. At the margin, for the last project that the firm takes, its net present value should be zero.

For asset prices, equation (1) says that the cost of capital should vary cross-sectionally, depending on investment, expected profitability, and expected investment growth. In a two-period setup, equation (1) says $r_{t+1} = (X_{t+1} + 1 - \delta)/(1 + aI_t/A_t)$. All else equal, low investment and high profitability stocks should earn higher expected returns than high investment and low profitability

[4] In particular, the three prominent behavioral theoretical studies on asset pricing anomalies all assume a constant discount rate (expected return), thereby attributing these anomalies entirely to predictable abnormal returns (Barberis, Shleifer, and Vishny 1998; Daniel, Hirshleifer, and Subrahmanyam 1998; Hong and Stein 1999).

[5] Liu, Whited, and Zhang (2009), for example, provide a detailed derivation of equation (1).

stocks, respectively (Hou, Xue, and Zhang 2015). In a multiperiod model, holding investment and profitability constant, the cost of capital also increases with expected growth. 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. 2020).

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 (expected profitability and expected growth) at bargain prices (low Tobin's q). This prescription is exactly identical to that in Graham and Dodd (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 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 Interpretation of Security Analysis

Despite similar prescriptions to equity analysts, our economics-based, equilibrium treatment on security analysis differs from Graham and Dodd's (1934) in a fundamental way. Predating equilibrium theory under uncertainty by three decades (Arrow 1964), 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, in the spirit of Ball (1978), we provide an economic model of cross-sectionally varying expected returns within efficient markets.

Within a historical context, the consumption CAPM rises up in the 1980s and 1990s to meet Shiller's (1981) excess volatility challenge and moves the needle from a constant discount rate to time-varying expected returns as the workhorse theory of efficient markets. We attempt to move the needle once again to cross-sectionally varying expected returns with the investment CAPM. Shiller attributes all of excess volatility to investor sentiment, whereas the consumption CAPM attributes it to time-varying expected returns. Analogously, Graham and Dodd (1934, 1940) attribute security analysis profits all to mispricing (the intrinsic-market value deviation), whereas the investment CAPM attributes the profits to cross-sectionally varying expected returns within efficient markets.

While departing from Graham and Dodd's (1934) mispricing perspective, we also deviate from traditional academic finance, which dismisses security analysis altogether. Instead, we embrace and systematically validate the practice of security analysis on equilibrium grounds, by directing analysts' attention to key expected return drivers, i.e., investment, profitability, and expected growth.

In general equilibrium, asset prices are determined jointly by demand and supply. In his magnum opus, Alfred Marshall (1890, [1961]) reconciles the costs of production theory with the marginal utility theory of value, using a famous "scissors" metaphor: "We might as reasonably dispute whether it is the upper or under blade of a pair of scissors that cuts a piece of paper, as whether value is governed by utility or costs of production. It is true that when one blade is held still, and the cutting is affected by moving the other, we may say with careless brevity that the cutting is done by the second; but the statement is not strictly accurate, and is to be excused only so long as it claims to be merely a popular and not a strictly scientific account of what happens (p. 348)."

The utility-based consumption CAPM and the production-based investment CAPM are the two "blades" that form the "scissors" of equilibrium asset pricing. The consumption CAPM arises from consumption Euler equation, while ignoring firms. As long as consumption, which is given exogenously, is consistent with the optimal behavior of firms left outside the model, consumption betas should be sufficient to price assets. The abstraction from investors in the investment CAPM is exactly symmetrical. The investment CAPM arises from investment Euler equation, while ignoring investors. As long as the pricing kernel is consistent with the optimal behavior of the marginal investor left outside the model, equation (1) should be sufficient to price assets. In general equilibrium, the consumption CAPM and the investment CAPM both hold and deliver identical expected returns.

Clearly, one needs both "blades" to fully grasp the "scissors" of equilibrium asset pricing. Covariance of returns with the pricing kernel plays a central role in the consumption CAPM, which does not directly model accounting variables. Symmetrically, characteristics play a leading role in the investment CAPM, which does not directly model covariance. 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, better portfolio optimization) than traditional asset pricing models. While the consumption CAPM largely fails 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 (issuer-focused) security analysis has long been perceived as diametrically opposite to (so far investor-focused) modern finance. In particular, honoring the 50th anniversary of Graham and Dodd (1934), Buffett (1984) reports the successful performance of 9 famous investors. After arguing that their success is beyond chance, Buffett writes: "Our Graham & Dodd investors, needless to say, do not discuss beta, the capital asset pricing model or covariance in returns among securities. These are not subjects of any interest to them. In fact, most of them would have difficulty defining those terms (p. 7)." This dichotomy is unfortunate, as demand and supply are the two "blades" that form Marshall's "scissors" of value theory.

Finally, 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)."

Alas, precisely because investors are left outside our model, we have little to say about the expected growth risk other than its potential accordance with some marginal investor's first principle. Kozak, Nagel, and Santosh (2018), for example, construct a model with distorted beliefs driving expected returns, but a factor model captures the cross section empirically. While our perspective on security analysis accords with efficient markets by connecting accounting information to expected returns in the spirit of Ball (1978), we emphasize that our evidence does not rule out distorted beliefs on the investor side. Rather, overturning 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 Prominent Security Analysis Strategies

We use the q^5 model as an empirical implementation of the investment CAPM to explain Frankel and Lee's (1998) intrinsic-to-market value (Section 3.1), Piotroski's (2000) fundamental score (Section 3.2), Greenblatt's (2005, 2010) "magic formula" (Section 3.3), Asness, Frazzini, and Pedersen's (2019) quality-minus-junk strategies (Section 3.4), Bartram and Grinblatt's (2018) agnostic strategies (Section 3.5), Penman and Zhu's (2014, 2018) fundamental strategies (Section 3.6), and Ball, Gerakos, Linnainmaa, and Nikolaev's (2020) retained earnings-to-market (Section 3.7).

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

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

Frankel and Lee (1998) estimate the intrinsic value from the residual income model and show that the intrinsic-to-market value forecasts returns. We follow exactly their measurement of the intrinsic value based on a two-period version of the residual income model at the end of June of each year t:

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

in which V_t^h is the intrinsic value, B_t the book equity, and $E_t[\text{Roe}_{t+1}]$ and $E_t[\text{Roe}_{t+2}]$ the expected returns on equity for the current and next fiscal year, respectively.[6]

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

[6] 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.

Table 1 shows that consistent with Frankel and Lee (1998), the intrinsic-to-market value shows some ability to predict returns. The high-minus-low V^h/P decile earns on average 0.28% per month, albeit insignificant ($t = 1.55$). Its q-factor and q^5 alphas are economically small and statistically insignificant. However, both are rejected by the GRS test on the null that the alphas are jointly zero across the deciles. The predictability is stronger in quintiles, which yield an average high-minus-low return of 0.43% ($t = 2.79$). The quintile spread does not vary much with size, with 0.27%, 0.35%, and 0.36% ($t = 2.01$, 2.25, and 2.29) across micro, small, and big stocks, respectively.[7]

The q-factor and q^5 models do a good job in the two-way sorts. The q-factor alphas of the high-minus-low quintiles are 0.13%, 0.18%, and 0.17% per month ($t = 0.94$, 1.13, and 1.07) across micro, small, and big stocks, and their q^5 alphas 0.13%, 0.13%, and 0.11% ($t = 1.05$, 0.88, and 0.68), respectively. Neither model can be rejected by the GRS test on the null that the alphas are jointly zero across the 3×5 portfolios. The investment factor is the key driving force behind the explanatory power. In the q^5 regressions, the investment factor loadings of the high-minus-low quintiles are 0.5, 0.7, and 0.72 ($t = 4.8$, 5.38, and 5.77) across micro, small, and big stocks, respectively. In contrast, their Roe and expected growth factor loadings are economically small and statistically insignificant.[8]

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 invest-

[7] Frankel and Lee (1998) also calculate an analysts' forecast-based intrinsic value, V_t^f, in which the Roe expectations are computed with analysts earnings forecasts from IBES. In untabulated results, we show that V^f/P shows only weak predictive power of returns. From July 1976 onward (when analysts' forecasts become available), the high-minus-low decile earns on average 0.35% per month ($t = 1.63$), and the high-minus-low quintile 0.13% ($t = 0.72$). Also, the quintile spreads are 0.18%, 0.08%, and 0.11% ($t = 0.92$, 0.39, and 0.59) across micro, small, and big stocks, respectively.

[8] The Fama-French (2018) 6-factor model (with the market factor, MKT; a size factor, SMB; a value factor, HML; an operating profitability factor, RMW; an investment factor, CMA; and a momentum factor, UMD) also explains the intrinsic-to-market anomaly. The high-minus-low quintile alphas are 0.14%, 0.11%, and 0.01% per month ($t = 1.36$, 1.02, and 0.12) across micro, small, and big stocks, respectively. The 6-factor model can be rejected by the GRS test with the deciles ($p = 0.04$) but not with the 15 two-way portfolios ($p = 0.43$) (the Internet Appendix, Table S1).

ment, 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), empirically, the investment factor is the key force driving.

More generally, 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). Unfortunately, intrinsic value estimates can be very sensitive to the assumed discount rates. As such, we interpret the Frankel-Lee intrinsic value estimates in equation (2), which assumes a constant discount rate of 12%, mainly as a nonlinear function of investment, profitability, and expected growth.

3.2 Piotroski's (2000) Fundamental Score Strategies

Piotroski (2000) shows that a fundamental analysis strategy is highly effective when applied to a sample of high book-to-market firms. Piotroski chooses nine fundamental signals to measure a firm's profitability, liquidity, and operating efficiency. Each signal is classified as good or bad (one or zero), depending on its implications for future stock prices and profitability. The fundamental score, denoted F, is the sum of the nine binary signals. All the accounting variables in the F-score construction are from Compustat Annual Fundamental Files (the Internet Appendix).

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

Panel A of Table 2 shows that the F-score predictability is mixed in our extended sample. The high-minus-low portfolio earns on average only 0.28% per month ($t = 1.09$).[9] The evidence is stronger in quintiles, which yield an average high-minus-low return of 0.3% ($t = 1.97$). Across micro, small, and big stocks, the quintile spreads are 0.5%, 0.36%, and 0.28% ($t = 3.25$, 2.5, and 1.78), respectively. The q-factor and q^5 models largely explain this predictability. The q-factor alphas of the high-minus-low quintiles are 0.23%, 0.1%, and 0.12% ($t = 1.56$, 0.85, and 0.84), and the q^5 alphas 0.33%, 0.1%, and 0.03% ($t = 2.67$, 0.81, and 0.15), respectively. Although the GRS test rejects the q-factor model with the 15 two-way portfolios ($p = 0.01$), it cannot reject the q^5 model ($p = 0.09$).[10]

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

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

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[9] In untabulated results, we show that restricting the sample to the top book-to-market quintile per Piotroski (2000) yields even weaker evidence, as the high-minus-low portfolio earns only 0.2% ($t = 0.54$). Sampling variation plays an important role. If we end the sample in December 1998, which is close to Piotroski's original sample, the average high-minus-low return for the top book-to-market quintile is 0.76%, albeit still insignificant ($t = 1.7$). From January 1999 onward, the average return is −0.54% ($t = -0.88$). Sampling variation is less extreme in our full sample, which includes all book-to-market quintiles. The average high-minus-low return is 0.51% ($t = 1.69$) and −0.03% ($t = -0.07$) before and after December 1998, respectively.

[10] The Fama-French 6-factor model also captures the F-score anomaly. The high-minus-low quintile alphas are 0.3%, 0.2%, and 0.13% per month ($t = 2.79$, 1.75, and 0.94) across micro, small, and big stocks, respectively. However, the model is rejected by the GRS test with the 15 two-way portfolios ($p = 0.02$) (the Internet Appendix, Table S2).

with two values (0 and 1). Doing so likely understates the heterogeneity across firms and dampens the predictive power relative to the Roe factor, which is built on continuous Roe values.

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

In a popular book titled "The little book that beats the market," Greenblatt (2005) proposes a "magic formula" that embodies Warren Buffett and Charlie Munger's interpretation of the Graham-Dodd (1934) philosophy. The basic idea is to buy good companies (ones that have high returns on capital) at bargain prices (prices that give 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.[11] At the end of June of each year t, we form a composite score by averaging the percentiles of return on capital and earnings yield for the fiscal year ending in calendar year $t-1$ and sort stocks into deciles based on the NYSE breakpoints of the composite score. Monthly value-weighted returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of year $t+1$. For two-way sorts, at the end of June of year t, we sort stocks into quintiles based on the NYSE breakpoints of the composite score for the fiscal year ending in calendar year $t-1$. Independently, we sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the June-end market equity. Taking intersections yields 15 portfolios.

Table 3 shows that the Greenblatt measure forecasts returns reliably. In one-way sorts, the high-minus-low decile earns on average 0.67% per month ($t = 3.01$). In two-way sorts with size, the high-minus-low quintiles earn on average 0.43%, 0.47%, and 0.47% ($t = 2.51$, 2.87, and 3.08) across micro,

[11] 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.

small, and big stocks, respectively. The q-factor and q^5 models largely explain the Greenblatt formula. The high-minus-low decile has a q-factor alpha of 0.26% ($t = 1.51$) and a q^5 alpha of -0.13% ($t = -0.76$). The high-minus-low quintile has q-factor alphas of 0.05%, 0.08%, and 0.19% ($t = 0.29$, 0.56, and 1.41) and q^5 alphas of 0.06%, 0.03%, and -0.11% ($t = 0.43$, 0.18, and -0.84) across micro, small, and big stocks, respectively. The GRS test cannot reject the q-factor or q^5 model.[12]

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 or the full sample. 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. Also, the earnings yield is a value metric, which gives rise to the role of 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, and show that 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. Accordingly, we form the quality score as the average of the profitability, growth, and safety scores.[13]

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 the fiscal year ending in calendar

[12]The Fama-French 6-factor model also largely explains the Greenblatt measure. The 6-factor alphas of the high-minus-low quintiles are 0.15%, 0.11%, and 0.13% per month ($t = 1.37$, 1.15, and 1.07) across micro, small, and big stocks, respectively. In addition, the model cannot be rejected by the GRS test (the Internet Appendix, Table S3).

[13]We measure profitability as 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 then standardized into a z-score. Standardization means that we divide the cross-sectionally demeaned values of the rankings by their cross-sectional standard deviation. The profitability score is the average of the individual z-scores of the six profitability measures. We measure growth as the 5-year growth in residual per-share profitability measures, excluding accruals. The growth score is the average of the individual z-scores of the five growth measures. Finally, we measure safety with the Frazzini-Pedersen (2014) beta, leverage, O-score, Z-score, and the volatility of return on equity. The safety score is the average of the individual z-scores of the five safety measures (the Internet Appendix).

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.

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 0.33% per month but is only marginally significant ($t = 1.66$).[14] The q-factor model fails to explain this spread, with an alpha of 0.44% ($t = 3.28$), and the model is rejected by the GRS test on the null that the alphas across the quality deciles are jointly zero ($p = 0.00$). In contrast, the q^5 model yields a tiny alpha of 0.06% ($t = 0.42$), and the GRS test fails to reject the q^5 model ($p = 0.12$). In the q^5 regression, the quality-minus-junk decile has significantly negative market, size, and investment factor loadings, which go in the wrong way in explaining the average return. Going in the right direction, the quality-minus-junk decile also has significantly positive Roe and expected growth factor loadings.

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

[14] 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 (that we view as more standard). The estimate in our reproduction with their sample criteria is 0.41% ($t = 2.1$).

and expected growth factor loadings are sufficiently powerful to yield small q^5 alphas. However, the q^5 model is still rejected by the GRS test across the 15 two-way portfolios ($p = 0.00$).[15]

Asness, Frazzini, and Pedersen (2019) also construct an alternative quality score as the average of the profitability, growth, safety, and payout scores. The payout z-score is the average of the z-scores based on the rankings of equity net issuance, debt net issuance, and total net payout over profits (the Internet Appendix). Because the quality-minus-junk factor posted on the AQR Web site contains the payout component,[16] 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 S5). The high-minus-low alternative decile earns on average 0.5% per month ($t = 2.68$). The q^5 model shrinks the alpha to 0.1% ($t = 0.84$), and the GRS test cannot reject the model ($p = 0.18$). The alternative quality premium also varies inversely with size, 0.72%, 0.45%, and 0.36% per month ($t = 4.39$, 3.3, and 2.71) across micro, small, and big stocks, respectively. Except for microcaps, in which the alpha is 0.33% ($t = 2.54$), the q^5 alpha is small in the broad cross section, 0.08% ($t = 0.73$) in small stocks and 0.04% ($t = 0.43$) in big stocks. 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 but with a smaller magnitude. However, the q^5 model is still rejected by the GRS test across the 15 two-way portfolios ($p = 0.00$).[17]

The Internet Appendix also shows results on strategies formed separately on the profitability, growth, safety, and payout scores (Table S7–S10). Without going into the details, the average returns of the high-minus-low deciles on the profitability, growth, safety, and payout scores are 0.37%,

[15]The Fama-French 6-factor model largely fails to explain the quality premium. In one-way sorts, the quality-minus-junk decile has a 6-factor alpha of 0.52% per month ($t = 3.96$). In two-way sorts, across micro, small, and big stocks, the quality-minus-junk quintiles have 6-factor alphas of 0.49%, 0.35%, and 0.38% ($t = 4.36$, 3.53, and 3.49), respectively. The GRS test strongly rejects the 6-factor model with either sorts ($p = 0.00$) (the Internet Appendix, Table S4).

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

[17]The Fama-French 6-factor model largely fails to explain the alternative quality premium. In one-way sorts, the quality-minus-junk decile has an alpha of 0.56% per month ($t = 4.47$). In two-way sorts, the quality-minus-junk quintiles have alphas of 0.54%, 0.33%, and 0.4% ($t = 4.68$, 3.49, and 3.94) across micro, small, and big stocks, respectively. The GRS test strongly rejects the model with either sorts ($p = 0.00$) (the Internet Appendix, Table S6).

0.18%, 0.2%, and 0.47% per month ($t = 2.11$, 1.12, 0.96, and 2.79), respectively. The q^5 alphas are mostly insignificant, −0.01%, 0.31%, 0.16%, and −0.09 ($t = -0.1$, 2.17, 1.05, −0.67), respectively.[18]

The high-minus-low growth decile has a tiny market beta, a negative size factor loading of −0.35, and positive Roe and expected growth factor loadings of 0.37 and 0.24, respectively. However, the investment factor loading is large, −1.12 ($t = -12.03$), which pushes up the q^5 alpha to 0.31% ($t = 2.17$). Intuitively, the growth score measures the past 5-year growth rates in profits, earnings, and cash flows, all of which are positively correlated with past asset growth (investment), giving rise to a strongly negative loading on our 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 Fundamental Analysis Strategies

Bartram and Grinblatt (2018) show that the deviation of a firm's peer-implied intrinsic value from its market value forecasts returns reliably. Instead of relying on the residual income model, Bartram and Grinblatt estimate a stock's intrinsic value as the fitted component from monthly cross-sectional regressions via ordinary least squares of the stock's market equity, P, on 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.[19] The sample starts in January 1977

[18]The Fama-French 6-factor alphas of these zero-investment deciles are 0.36%, 0.48%, 0.43%, and 0.1% per month ($t = 3.19$, 4.12, 2.87, and 1.02), respectively (the Internet Appendix, Tables S11–S14).

[19]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.

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 four months ago).[20] A stock's intrinsic value, V, each month, is given by the fitted component of the month's cross-sectional regression, and the agnostic fundamental measure is defined as the percentage deviation of the intrinsic value from the market value, $(V-P)/P$.

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

Panel A of Table 5 reports the one-way sorts. The agnostic measure predicts return reliably. The high-minus-low decile earns on average 0.48% per month ($t = 2.88$). The q-factor alpha is 0.32% per month ($t = 1.47$), but the q^5 alpha is 0.47% ($t = 2.22$). The GRS test rejects the q-factor model but not the q^5 model. In the q^5 regression, the high-minus-low decile loads positively on the investment factor, 0.61 ($t = 4.24$), going in the right direction, but loads negatively on the expected growth factor, -0.23 ($t = -1.98$), going in the wrong direction in explaining the average return. The size factor also helps with a loading of 0.29 ($t = 2.79$), but the market and Roe factor loadings are tiny.

From Panel B, the q-factor and q^5 models do a better job in the two-way sorted portfolios. The high-minus-low agnostic quintiles earn on average 0.92%, 0.5%, and 0.46% per month ($t = 4.25$, 2.42, and 2.11) across micro, small, and big stocks, respectively. The q-factor model mostly reduces

[20]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.

the average returns to insignificance, with alphas of 0.54%, 0.21%, and 0.33% ($t = 2.03$, 0.85, and 1.23), and the q^5 model does too, with alphas of 0.48%, 0.27%, and 0.42% ($t = 1.82$, 1.23, and 1.7), respectively.[21] The investment factor loadings are economically large and highly significant, but the Roe and expected growth factor loadings are mostly insignificant, with mixed signs.[22]

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

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

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

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

Penman and Zhu (2014) forecast the forward earnings yield, Y_{it+1}/P_{it}, and the 2-year-ahead earnings growth with several anomaly variables, many of which forecast the forward earnings yield and earnings growth in the same direction of forecasting returns. Penman and Zhu (2018) construct a fundamental analysis strategy based on the expected return proxy from projecting future returns

[21]The Fama-French 6-factor alphas of the high-minus-low agnostic quintiles are 0.67%, 0.27%, and 0.31% per month ($t = 3.02$, 2.15, and 2.13) across micro, small, and big stocks, respectively (the Internet Appendix, Table S15).

[22]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 S16). The results are largely similar. The high-minus-low agnostic decile earns a somewhat higher average return of 0.63% per month ($t = 3.41$), but its q^5 alpha is 0.38% ($t = 1.99$). The high-minus-low quintiles earn on average 0.81%, 0.47%, and 0.37% ($t = 3.7$, 2.26, and 1.7) across micro, small, and big stocks, respectively. The q-factor and q^5 alphas become larger and more significant in microcaps but remain relatively small and insignificant in small and big stocks.

on anomaly variables that are a priori connected to future earnings growth. The expected return proxy, denoted ER8, is based on eight variables. We work with ER8 because it is the most comprehensive proxy in their study. The eight variables consist 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).

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

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

Table 6 reports the results. From Panel A, the high-minus-low ER8 decile earns on average 0.69% per month ($t = 3.79$). While the q-factor model fails to explain the average return, with an alpha of 0.55% ($t = 3.32$), the q^5 model shrinks the alpha to 0.25% ($t = 1.5$). In the q^5 regression, the investment factor loading is 0.66 ($t = 6.66$), and the expected growth factor loading 0.46 ($t = 4.23$). Intuitively, ER8 contains two value metrics, earnings-to-price and book-to-market, which correlate negatively with investment, due to the investment-value linkage (Section 3.1). In addition, Penman and Zhu (2018) select the eight variables based on their predictive power of earnings growth. Because earnings growth and investment growth tend to be positively correlated, the high-minus-low ER8 decile loads positively on the expected investment growth factor.

From Panel B, the ER8 premium varies inversely with size. The high-minus-low quintiles earn on average 0.78%, 0.33%, and 0.48% ($t = 4.82$, 2.24, and 3.29) across micro, small, and big stocks, respectively. The q^5 alpha is 0.55% ($t = 3.23$) in microcaps but insignificant in small stocks, 0.01% ($t = 0.09$), and in big stocks, 0.16% ($t = 1.25$).[23] While the investment factor loadings are consistently large and significant, the expected growth factor loading is significant only in big stocks.

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

While the investment CAPM seems more appealing on economic grounds, it should be emphasized that the theory assumes perfect accounting, which does not exist in reality. In particular, profitability, X_{it}, is economic profitability, which does not capture any negative impact of accruals (earnings management). Also, investment includes all investing activities that increase future earnings, such as research and development, advertising, and employee training. As such, the ac-

[23]The Fama-French 6-factor alphas of the high-minus-low quintiles are 0.6%, 0.11%, and 0.33% ($t = 4.57$, 1.07, and 2.63) across micro, small, and big stocks, respectively (the Internet Appendix, Table S17).

counting insights of Penman and Zhu (2014, 2018) are missing from the investment CAPM. These insights are especially important for our empirical implementation. In fact, the expected growth factor in the q^5 model is partially motivated by their accounting insights (Hou et al. 2020).

3.7 Ball, Gerakos, Linnainmaa, and Nikolaev's (2020) Retained Earnings-to-Market

Ball et al. (2020) argue that book-to-market strategies work because the retained earnings component of the book equity averages out transitory shocks to past earnings, not because the book equity is a good indicator of intrinsic value. In particular, retained earnings, when scaled by the market equity, is a good proxy for the underlying earnings yield, which is tied to expected returns (Ball 1978).

Following Ball et al.'s (2020), we measure retained earnings as retained earnings (Compustat annual item RE) minus accumulated other comprehensive income (item ACOMINC, zero if missing).[24] At the end of June of year t, we split stocks into deciles with the NYSE breakpoints of retained earnings for the fiscal year ending in calendar year $t-1$ scaled by its December-end market equity. For two-way sorts, we split stocks into quintiles on retained earnings-to-market, 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 $t+1$.

From Table 7, the high-minus-low decile earns on average 0.47% per month ($t = 2.23$). The q and q^5 models both yield small alphas, 0.06% ($t = 0.3$) and -0.14% ($t = -0.7$), respectively. In two-way sorts, the high-minus-low quintile earns on average 0.57%, 0.44%, and 0.43% ($t = 2.81, 2.3$, and 2.38), and the q^5 model largely explains the return spreads, with alphas of 0.1%, -0.06%, and -0.28% ($t = 0.63, -0.42$, and -1.7), respectively. The q-factor alphas are largely similar. However, both models are still rejected by the GRS test. The investment factor is the key driving force, with economically large and highly significant loadings. The other loadings are mostly insignificant.[25]

[24] Compustat annual item ACOMINC starts only in 1987. Ball et al. (2020) do not explain how missing values in early years are treated. By setting the missing observations to zero, we are able to replicate their estimates very closely.

[25] The Fama-French 6-factor model explains well the retained earnings-to-market deciles. The high-minus-low decile

Ball et al. (2020) apply Ball's (1978) earnings yield argument to scale retained earnings by the market equity to explain the value premium. Relatedly, Ball et al. (2016) argue that operating cash flow is a better proxy for economic 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 verify this conjecture. The portfolio construction is analogous to that in Table 7, except that we sort on operating cash flow-to-market (the numerator is from the fiscal year ending in calendar year $t-1$ and the market equity is from the December-end of year $t-1$).[26]

Table 8 shows that consistent with Ball (1978), operating cash flow-to-market is a very strong predictor of returns. The high-minus-low decile earns on average 0.92% per month ($t = 4.52$)! The q-factor model leaves unexplained a large alpha of 0.58% ($t = 3.49$). The q^5 model largely explains the return spread with a small alpha of 0.15% ($t = 0.9$), and the model cannot be rejected by the GRS test ($p = 0.86$). In the two-way sorts, the high-minus-low quintile earns on average 0.93%, 0.69%, and 0.46% ($t = 6.55, 4.25$, and 2.57), and their q^5 alphas are 0.44%, 0.08%, and −0.08% ($t = 3.31, 0.58$, and −0.52), respectively. As such, except for microcaps, the q^5 model largely explains the return spreads. Both the investment and expected growth factor loadings are economically large and statistically significant, with mixed signs for the Roe factor loadings. However, the model is still rejected by the GRS test with the 15 two-way portfolios ($p = 0.01$).[27]

has only a small alpha of −0.06% per month ($t = -0.39$), and the model is not rejected by the GRS test ($p = 0.15$). In the two-way sorts, the high-minus-low quintiles have insignificant alphas in micro, small, and big stocks, but the model is still rejected by the GRS test with the 15 two-way portfolios ($p = 0.01$) (the Internet Appendix, Table S18).

[26] Following Ball et al. (2016), we measure operating cash flow at the June-end of year t 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.

[27] The Fama-French 6-factor model yields an alpha of 0.41% per month ($t = 2.89$) for the high-minus-low decile, and the model is rejected by the GRS test with the deciles ($p = 0.01$). In two-way sorts, the high-minus-low quintile has 6-factor alphas of 0.54%, 0.22%, and −0.03% ($t = 5.2, 2.11$, and −0.2), respectively, and the model is again rejected by the GRS test with the 15 two-way portfolios ($p = 0.00$) (the Internet Appendix, Table S19).

4 Explaining the Performance of Active Value Funds

The strategies in Section 3 are all quantitative. Sloan (2019) argues that quantitative strategies tend to select stocks based on distorted accounting numbers and overlook important, qualitative information that active, discretionary managers exploit. To mitigate this concern, we examine Buffett's Berkshire in Section 4.1 and best-performing active value funds in Section 4.2. Going beyond a few quantitative signals, the strategies of these discretionary funds might not be easily quantifiable.

4.1 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 2018. The observations prior to November 1976, in January and February 1977, in March and April 1978, and in May and June 1979 are from Compustat, and the remainder from CRSP.[28]

In the 1968–2018 sample, Berkshire's excess return is on average 1.44% per month ($t = 4.96$). The q-factor model reduces the average return by 56% to an alpha of 0.64%, albeit still significant ($t = 2.44$), aided by large investment and Roe factor loadings of 0.58 ($t = 3.61$) and 0.42 ($t = 3.46$), 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 Buffett's well known philosophy of buying profitable firms at bargain prices.

The expected growth factor loading in the q^5 regression is -0.2, albeit insignificant ($t = -1.11$), going in the wrong direction as the average return to yield a higher q^5 alpha of 0.77% ($t = 2.67$). The evidence indicates Buffett's reluctance in investing high expected growth stocks, likely because of their relatively high valuation (and uncertainty with future growth). We emphasize that value (investment) and expected growth are two distinct factors in the q^5 model. As noted, past growth mostly measures value, as opposed to expected growth (Section 3.4). Also, the q^5 model features two

[28]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.

related but different aspects of quality, expected profitability and expected growth. Our evidence indicates that Buffett's "circle of competence" focuses on evaluating the quality of mature industries but not necessarily the quality of 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 remains challenging even for the best value investor.

Frazzini, Kabiller, and Pedersen (2018) show that Buffett's alpha in Berkshire becomes insignificant in the AQR 6-factor model. Their table 4 reports that from November 1976 to March 2017, Berkshire earns an insignificant alpha of 0.45% per month ($t = 1.55$). Panel B of Table 9 reproduces their evidence. We obtain an AQR 6-factor alpha of 0.46% per month ($t = 1.69$) in the same sample period. Our loadings are also close to their original estimates. However, once we extend the sample backward to February 1968, the AQR 6-factor alpha rises to 0.61% ($t = 2.08$).[29]

4.2 Best-performing Active Value Funds

We next examine best-performing active value funds. Similar to Buffett's Berkshire, these active, discretionary funds follow security analysis strategies that go beyond a few quantitative signals. We show that the q^5 model goes a long way in explaining the performance of these active 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). We identify value funds via lowercase fund names

[29]The Fama-French 6-factor model underperforms the q-factor and the AQR 6-factor models in explaining Buffett's alpha. The Fama-French alpha is 0.69% per month ($t = 2.43$) in the shorter sample from November 1976 onward and 0.82% ($t = 2.98$) in the longer sample from February 1968 onward (the Internet Appendix, Table S20). 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 examined the evidence with Compustat's Berkshire returns prior to September 1988. The results are quantitatively close (the Internet Appendix, Table S21).

that contain the exact word "value" (Lettau, Ludvigson, and Manoel 2019).[30] Because funds can switch styles, we exclude the periods when funds drop out of the domestic value category.

To select only active value 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.[31] For funds with multiple share classes, we link the share classes via the MFLINKS table from Wharton Research Data Services (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). We also require non-missing net fund returns and expense ratios to compute gross fund returns. Our aggregate portfolio of domestic active value funds covers 860 unique funds from January 1986 to December 2018. We start in 1986 to have at least 10 funds in each month.

We select top 20 active funds based on their full-life monthly geometric average gross returns. Full-life includes months before 1986 and with TNA below $15 million. We exclude funds that do not have the complete history between their first and last months. We require a minimum track record of 10 years. We include both live and dead funds. There exist 409 unique value funds with an uninterrupted track record of at least 10 years. As such, top 20 amounts to about 5%. Finally, choosing top funds based on their complete histories (full-life compounded gross returns) induces hindsight bias in their selection. However, as in the case for Buffett's Berkshire, such hindsight bias goes against factor models in explaining the performance of ex post best-performing funds.

Table 10 lists the top-20 active value funds in the CRSP database. The best-performing fund is Morgan Stanley Dean Witter American Value, which earns a monthly geometric average gross

[30] We filter out names with words such as "values" and "valued" that do not identify value funds. We do not use CRSP value style codes due to missing data prior to December 1999. The codes can also lead to incorrect identification.

[31] 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."

return of 1.65% per month from December 1987 to November 1999. Net of expenses, the monthly geometric average net return is 1.53%. Its time series average monthly TNA is $1,884.33 million. This TNA is relatively large. Among the 409 active value funds with an uninterrupted record of at least 10 years, the mean TNA is $943 million, and median $360 million. The best fund's TNA resides between the 75th percentile, $985 million, and the 90th percentile, $2,374 million. The largest top-20 fund is T. Rowe Price Small-Cap Value Fund, with an average TNA of $4,393.81 million, which is larger than the 95th percentile of $3,762 million. Its monthly geometric average gross return of 1.04% from December 1990 to December 2018 ranks 9th on the top-20 list. Finally, the smallest fund on the list is Eaton Vance Tax-Managed Small-cap Value Fund, with only a TNA of $31.53 million, which lies between the 5th percentile of $25 million and the 10th percentile of $46 million. Its average gross return of 0.97% from October 2002 to June 2015 ranks at the bottom of the list.

Panel A of Table 11 shows that the aggregate equal-weighted portfolio of all active value funds earns an average gross return (in excess of the riskfree rate) of 0.67% per month ($t = 2.93$). However, consistent with Sharpe's (1991) arithmetic of active management, the CAPM alpha is only 0.06% ($t = 0.74$). As such, the average fund barely beats the market portfolio before fees. The q^5 alpha is negative, −0.09% ($t = -1.62$), indicating a small amount of underperformance. The equal-weighted aggregate portfolio has large and significant market, size, and investment factor loadings. The Roe factor loading is small, albeit significant, and the expected growth factor loading is tiny. The evidence with the TNA-wighted fund portfolio is largely similar. From Panel B, net of fees, the equal-weighted fund portfolio earns 0.58% ($t = 2.52$), with a small negative CAPM alpha of −0.03%. However, this portfolio underperforms the q^5 model with a significant alpha of −0.18% ($t = -3.39$).

The top-20 funds represent a high hurdle for the q^5 model. The equal-weighted top-20 fund portfolio earns an average gross excess return of 0.95% per month ($t = 4.28$), which yields a CAPM alpha of 0.41% ($t = 3.71$). The q^5 model shrinks the average return to an alpha of 0.29%, which represents a reduction of 69.5% in magnitude, although the alpha remains significant ($t = 3.96$). The market, size, and investment factor loadings are all large and significant, whereas the Roe and expected growth factor loadings are tiny. For the TNA-weighted top-20 fund portfolio, the q^5 model reduces the average excess return, 0.86% ($t = 3.92$), to an alpha of 0.19% ($t = 2.74$), a reduction of 77.9% in magnitude. Net of fees, the equal-weighted portfolio earns on average 0.83% ($t = 3.73$). The q^5 model yields an alpha of 0.16% ($t = 2.25$), a reduction of 80.7% in magnitude from the average excess return. For the TNA-weighted portfolio, its average excess return is 0.74% ($t = 3.41$), but the q^5 alpha is only 0.08% ($t = 1.15$), which represents a reduction of 89.2%.

The remainder of Table 11 shows the q^5 regression for each of the top-20 funds. From Panel A, the average gross excess returns range from 0.6% ($t = 2$) to 1.32% per month ($t = 3.8$) across the top-20 funds.[32] The q^5 alphas vary from -0.06% ($t = -0.52$) to 0.58% ($t = 1.49$). Only 4 out of 20 q^5 alphas are significant at the 5% level. Panel B shows that net of fees, the average net excess returns range from 0.45% ($t = 1.51$) to 1.21% ($t = 3.3$). The q^5 alphas vary from -0.19% ($t = -1.56$) to 0.48% ($t = 1.24$), and only 2 out of 20 q^5 alphas are significant.

The market, size, and investment factors combine to explain the top-20 funds' performance, with the Roe and expected growth factors playing a secondary role. For the q^5 regressions with gross returns, all 20 market betas, 16 size factor loadings, and 14 investment factor loadings are significantly positive. A notable exception is the 7th ranked fund (Royce Value Plus Fund), with an investment factor loading of -0.49 ($t = -5.98$). The Roe and expected growth factor loadings are mostly insignificant, with mixed signs. The evidence with net return regressions is largely similar.[33]

5 Conclusion

In the investment CAPM, expected returns vary cross-sectionally, depending on firms' investment, expected profitability, and expected growth. While realized returns are predictable, abnormal returns are not, thereby retaining efficient markets. As an empirical implementation of the investment CAPM, the q^5 model goes a long way toward explaining the performance of prominent

[32]The average gross excess returns in Table 11 are simple returns, which are appropriate for factor regressions. These returns differ from the geometric average raw returns in Table 10 used to rank the full-life performance of funds.

[33]The Fama-French 6-factor alphas are largely similar to the q^5 alphas. The equal-weighted top-20 portfolio has an alpha of 0.27% ($t = 4.61$) gross of fees and an alpha of 0.14% ($t = 2.46$) net of fees (the Internet Appendix, Table S22).

security analysis strategies, such as Frankel and Lee's (1998) intrinsic-to-market value, Piotroski's (2000) fundamental score, Greenblatt's (2005) "magic formula," Asness, Frazzini, and Pedersen's (2019) quality-minus-junk, Bartram and Grinblatt's (2018) agnostic fundamental analysis, Penman and Zhu's (2014, 2018) expected return strategies, and Ball, Gerakos, Linnainmaa, and Nikolaev's (2020) retained earnings-to-market, as well as best-performing active value funds, such as Warren Buffett's Berkshire. In all, the evidence suggests that the investment CAPM is a good start to reconciling Graham and Dodd's (1934) *Security Analysis* with Fama's (1970) efficient markets.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

The Internet Appendix details the agnostic fundamental measure, $(V-P)/P$, which is the deviation of the estimated intrinsic value from the market equity as a fraction of the market equity. In Panel A, at the beginning of each month t, we sort stocks into deciles based on the NYSE breakpoints of the agnostic measure constructed with firm-level variables from at least four months ago. Monthly value-weighted decile returns are calculated from the current month t, and the deciles are rebalanced at the beginning of month $t+1$. 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}
$\overline{R}$	0.58	0.52	0.62	0.51	0.81	0.81	0.86	0.90	1.00	1.06	0.48	
$t_{\overline{R}}$	2.02	2.10	3.10	2.86	3.90	3.95	3.73	3.62	3.68	3.48	2.88	
α_q	0.09	−0.01	0.04	0.07	0.22	0.20	0.19	0.19	0.27	0.41	0.32	0.04
t_q	0.76	−0.09	0.48	0.70	2.72	1.77	1.35	1.18	1.62	2.15	1.47	
α_{q^5}	0.05	−0.05	−0.01	−0.03	0.14	0.19	0.28	0.30	0.36	0.52	0.47	0.05
t_{q^5}	0.42	−0.42	−0.17	−0.24	1.65	1.62	1.99	1.86	2.36	3.07	2.22	
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.03	0.29	0.61	−0.10	−0.23		−0.47	2.79	4.24	−0.69	−1.98	0.18

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

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.57	0.57	0.82	0.87	1.02	0.45		2.29	3.11	4.12	3.73	3.65	2.17
Micro	0.20	0.36	0.83	0.82	1.11	0.92		0.48	1.00	2.49	2.73	3.44	4.25
Small	0.58	0.85	0.84	0.98	1.08	0.50		1.73	3.00	3.12	3.63	3.59	2.42
Big	0.58	0.57	0.83	0.87	1.04	0.46		2.37	3.16	4.23	3.79	3.78	2.11
			α_q ($p_{\text{GRS}}=0.00$)							t_q			
All	0.06	0.07	0.22	0.19	0.31	0.25		0.54	1.01	3.17	1.36	1.84	0.95
Micro	−0.10	−0.26	0.08	0.00	0.44	0.54		−0.37	−1.34	0.48	−0.01	2.16	2.03
Small	0.06	0.13	0.03	0.14	0.27	0.21		0.52	1.41	0.34	1.10	1.62	0.85
Big	0.07	0.08	0.25	0.24	0.41	0.33		0.64	1.16	3.40	1.56	2.24	1.23
			α_{q^5} ($p_{\text{GRS}}=0.00$)							t_{q^5}			
All	0.03	−0.03	0.18	0.28	0.41	0.38		0.24	−0.42	2.26	2.04	2.71	1.66
Micro	−0.02	−0.27	−0.05	0.01	0.46	0.48		−0.06	−1.36	−0.27	0.08	2.55	1.82
Small	0.10	0.10	0.03	0.20	0.36	0.27		0.88	1.16	0.28	1.62	2.49	1.23
Big	0.05	−0.02	0.19	0.34	0.47	0.42		0.46	−0.32	2.40	2.19	2.71	1.70
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	0.07	0.30	0.78	−0.24	−0.21		0.93	1.43	3.95	−1.28	−1.50		0.21
Micro	0.03	−0.22	0.64	0.36	0.09		0.35	−2.21	3.43	1.64	0.49		0.20
Small	0.02	−0.37	1.00	0.11	−0.09		0.32	−2.13	5.70	0.54	−0.61		0.25
Big	0.11	0.07	0.70	−0.28	−0.13		1.58	0.37	3.73	−1.54	−0.84		0.12

Table 6 : The Penman-Zhu (2018) Fundamental Portfolios, Annually Formed, July 1982–December 2018

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

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

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

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

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

Table 7 : The Ball-Gerakos-Linnainmaa-Nikolaev (2020) Retained Earnings-to-market Portfolios, January 1967–December 2018

As in Ball et al. (2020), we measure retained earnings-to-market as retained earnings (Compustat annual item RE) minus accumulated other comprehensive income (item ACOMINC, zero if missing), scaled by the market equity (from CRSP). In Panel A, at the end of June of year t, we sort stocks into deciles based on the NYSE breakpoints of retained earnings for the fiscal year ending in calendar year $t-1$ scaled by its December-end market equity. 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 retained earnings for the fiscal year ending in calendar year $t-1$ scaled by its 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 $\beta_{\rm Mkt}$, $\beta_{\rm Me}$, $\beta_{\rm I/A}$, $\beta_{\rm Roe}$, 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 retained earnings-to-market

	L	2	3	4	5	6	7	8	9	H	H−L	$p_{\rm GRS}$
$\overline{R}$	0.35	0.33	0.55	0.48	0.70	0.68	0.70	0.83	0.79	0.83	0.47	
$t_{\overline{R}}$	1.26	1.41	2.76	2.75	3.96	4.05	3.69	4.63	4.03	3.70	2.23	
α_q	0.03	0.15	0.21	−0.09	0.12	0.02	−0.02	0.07	0.08	0.09	0.06	0.01
t_q	0.19	1.70	2.77	−1.23	1.78	0.23	−0.28	0.72	0.91	0.73	0.30	
α_{q^5}	0.14	0.26	0.04	−0.17	0.05	−0.13	−0.09	−0.02	0.00	0.00	−0.14	0.03
t_{q^5}	1.13	2.69	0.56	−1.88	0.75	−1.68	−1.08	−0.21	0.03	0.02	−0.70	
	$\beta_{\rm Mkt}$	$\beta_{\rm Me}$	$\beta_{\rm I/A}$	$\beta_{\rm Roe}$	$\beta_{\rm Eg}$		$t_{\rm Mkt}$	$t_{\rm Me}$	$t_{\rm I/A}$	$t_{\rm Roe}$	$t_{\rm Eg}$	R^2
H−L	−0.03	−0.08	1.22	−0.11	0.31		−0.47	−0.42	6.96	−0.61	2.12	0.28

Panel B: Quintiles from two-way independent sorts on size and retained earnings-to-market

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.31	0.51	0.70	0.74	0.82	0.51		1.25	2.84	4.14	4.14	4.10	2.88
Micro	0.49	0.70	0.90	1.09	1.05	0.57		1.33	2.50	3.42	4.13	3.95	2.81
Small	0.46	0.72	0.90	0.96	0.90	0.44		1.49	2.98	3.94	4.23	3.84	2.30
Big	0.33	0.51	0.68	0.72	0.76	0.43		1.38	2.86	4.13	4.03	3.87	2.38
			α_q ($p_{\rm GRS}=0.00$)							t_q			
All	0.09	0.05	0.08	0.00	0.10	0.01		0.94	0.95	1.32	0.05	1.14	0.10
Micro	0.01	0.01	0.18	0.32	0.15	0.14		0.08	0.07	1.64	3.83	1.30	0.74
Small	−0.06	0.03	0.10	0.08	−0.03	0.02		−0.62	0.60	1.52	0.89	−0.34	0.13
Big	0.15	0.07	0.08	−0.01	0.09	−0.07		1.60	1.25	1.28	−0.18	0.93	−0.43
			α_{q^5} ($p_{\rm GRS}=0.00$)							t_{q^5}			
All	0.20	−0.07	−0.03	−0.08	0.02	−0.18		2.16	−1.19	−0.57	−1.08	0.20	−1.20
Micro	0.05	0.03	0.21	0.31	0.15	0.10		0.37	0.41	2.03	3.38	1.42	0.63
Small	0.01	0.04	0.07	0.09	−0.05	−0.06		0.15	0.71	1.09	1.10	−0.56	−0.42
Big	0.28	−0.06	−0.04	−0.11	0.00	−0.28		2.81	−0.97	−0.56	−1.31	0.00	−1.70
	$\beta_{\rm Mkt}$	$\beta_{\rm Me}$	$\beta_{\rm I/A}$	$\beta_{\rm Roe}$	$\beta_{\rm Eg}$		$t_{\rm Mkt}$	$t_{\rm Me}$	$t_{\rm I/A}$	$t_{\rm Roe}$	$t_{\rm Eg}$		R^2
All	−0.02	0.17	1.22	−0.09	0.29		−0.42	1.88	10.77	−0.79	2.71		0.39
Micro	−0.14	−0.30	1.03	0.35	0.05		−2.50	−2.10	6.49	2.34	0.47		0.43
Small	−0.15	−0.17	1.22	0.11	0.13		−2.61	−1.32	9.03	0.80	1.19		0.45
Big	0.01	0.18	1.23	−0.14	0.31		0.22	2.03	10.57	−1.20	2.72		0.36

Table 8 : The Operating Cash Flow-to-market Portfolios, January 1967–December 2018

As in Ball et al. (2016), we measure operating cash flow, denoted Cop, at the June-end of year t as total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), plus research and development expenditures (item XRD, zero if missing), minus change in accounts receivable (item RECT), minus change in inventory (item INVT), minus change in prepaid expenses (item XPP), plus change in deferred revenue (item DRC plus item DRLT), plus change in trade accounts payable (item AP), and plus change in accrued expenses (item XACC), all 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 the ratio of Cop for the fiscal year ending in calendar year $t-1$ scaled by its December-end market equity (from CRSP). 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 retained earnings for the fiscal year ending in calendar year $t-1$ scaled by its 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. 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 operating cash flow-to-market

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.00	0.48	0.57	0.60	0.65	0.71	0.66	0.86	0.82	0.92	0.92	
$t_{\overline{R}}$	0.01	2.20	2.98	3.28	3.53	3.90	3.45	4.40	3.87	3.58	4.52	
α_q	−0.34	0.03	0.03	−0.02	−0.02	0.13	0.06	0.17	0.14	0.24	0.58	0.01
t_q	−3.37	0.28	0.41	−0.25	−0.21	1.60	0.62	1.99	1.29	1.88	3.49	
α_{q^5}	−0.02	0.04	0.02	−0.08	−0.09	−0.03	−0.11	0.02	0.05	0.13	0.15	0.86
t_{q^5}	−0.21	0.34	0.28	−0.90	−1.04	−0.39	−1.13	0.18	0.44	1.01	0.90	
	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	0.04	0.13	1.29	−0.57	0.65		1.00	1.75	8.54	−4.89	4.97	0.39

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	0.29	0.59	0.68	0.74	0.87	0.58		1.26	3.22	3.80	3.94	3.99	3.37
Micro	0.32	0.76	1.01	1.03	1.24	0.93		0.97	2.61	3.65	3.75	4.02	6.55
Small	0.31	0.86	0.92	1.02	1.00	0.69		1.04	3.43	3.77	4.05	3.63	4.25
Big	0.33	0.58	0.65	0.70	0.79	0.46		1.46	3.19	3.72	3.81	3.70	2.57
			α_q ($p_{\text{GRS}}=0.00$)							t_q			
All	−0.07	0.03	0.06	0.12	0.18	0.25		−0.92	0.43	0.92	1.47	1.93	1.85
Micro	−0.19	0.07	0.32	0.26	0.39	0.58		−1.61	0.79	3.64	3.34	3.70	4.42
Small	−0.24	0.06	0.08	0.13	0.03	0.26		−2.95	0.96	1.14	1.73	0.25	1.87
Big	0.01	0.04	0.05	0.10	0.14	0.13		0.12	0.57	0.77	1.17	1.31	0.89
			α_{q^5} ($p_{\text{GRS}}=0.01$)							t_{q^5}			
All	0.06	−0.02	−0.06	−0.05	0.08	0.02		0.79	−0.39	−0.88	−0.71	0.84	0.15
Micro	−0.11	0.09	0.27	0.24	0.33	0.44		−0.91	1.07	3.00	2.77	2.99	3.31
Small	−0.07	0.01	0.05	0.04	0.01	0.08		−0.91	0.18	0.73	0.47	0.08	0.58
Big	0.14	−0.01	−0.07	−0.07	0.06	−0.08		1.62	−0.17	−1.01	−0.88	0.48	−0.52
	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	0.03	0.26	1.08	−0.41	0.35		0.68	4.03	11.54	−4.36	3.46		0.38
Micro	0.01	−0.01	0.71	0.08	0.21		0.26	−0.25	7.33	0.75	2.60		0.27
Small	0.04	−0.03	1.05	−0.05	0.27		0.82	−0.31	9.48	−0.44	3.21		0.36
Big	0.03	0.23	1.11	−0.42	0.32		0.74	3.22	9.98	−3.85	2.88		0.34

Table 9 : Buffett's Alpha, February 1968–December 2018

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. For each sample period, we use the QMJ factor downloaded from the AQR Web site, denoted QMJ. 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
2/68–12/18	1.44	0.64	0.75	−0.03	0.58	0.42		0.17
	4.96	2.44	8.40	−0.21	3.61	3.46		
		0.77	0.73	−0.05	0.62	0.48	−0.20	0.18
		2.67	8.14	−0.30	3.79	3.48	−1.11	
11/76–3/17	1.51	0.48	0.87	−0.14	0.73	0.50		0.27
	4.81	1.75	10.30	−1.03	4.40	4.56		
		0.66	0.84	−0.16	0.78	0.60	−0.30	0.27
		2.10	9.70	−1.18	4.58	4.63	−1.46	

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
2/68–12/18	0.61	0.78	−0.11	0.30	−0.02	0.27	0.29	0.19
	2.08	8.21	−0.70	1.98	−0.24	2.65	1.91	
11/76–3/17	0.46	0.92	−0.18	0.38	−0.05	0.27	0.39	0.29
	1.69	10.62	−1.45	3.00	−0.93	3.04	2.81	

Table 10 : Top 20 Active Value Funds in the CRSP Mutual Fund Database

We select top 20 active funds based on their full-life performance measured as monthly geometric average gross returns (rret^g). To calculate the full-life performance, we include months before 1986 and with TNA below $15 million. We exclude funds that do not have the complete history 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 rret^g descending order, fund name, the start and end dates of a fund, the number of months in the database (#months), rret^g (in percent), monthly geometric average net returns (mret^g, in percent), and average monthly total net assets (TNA, in millions of dollar).

Rank	Fund Name	Start	End	#months	rret^g	mret^g	TNA
1	Morgan Stanley Dean Witter American Value	12/31/1987	11/30/1999	144	1.65	1.53	1884.33
2	AXA Enterprise Funds Trust: AXA Enterprise Small Company Value Fund	5/31/1997	5/31/2007	121	1.23	1.08	400.90
3	Meridian Fund, Inc: Meridian Value Fund	12/31/1994	8/31/2013	225	1.23	1.10	882.83
4	Oppenheimer Quest Value Fund, Inc	12/31/1980	11/30/2007	324	1.23	1.08	506.38
5	Smead Funds Trust: Smead Value Fund	12/31/2008	12/31/2018	121	1.20	1.15	608.11
6	Dreyfus Growth & Value Funds, Inc: Dreyfus Emerging Leaders Fund	12/31/1995	12/31/2006	133	1.18	1.07	722.22
7	Royce Fund: Royce Value Plus Fund	6/30/2003	4/30/2015	143	1.05	0.93	1620.58
8	Touchstone Strategic Trust: Touchstone Micro Cap Value Fund	12/31/1998	3/31/2013	172	1.04	0.91	80.07
9	T. Rowe Price Small-Cap Value Fund, Inc	12/31/1990	12/31/2018	337	1.04	0.96	4393.81
10	Wasatch Funds Trust: Wasatch Small Cap Value Fund	1/31/1998	12/31/2018	252	1.04	0.90	358.33
11	RBB Fund, Inc: Boston Partners Small Cap Value II Fund	12/31/1999	12/31/2018	229	1.04	0.91	266.48
12	AIM Sector Funds (Invesco Sector Funds): Invesco Special Value Fund	8/31/1999	4/30/2011	141	1.03	0.89	574.53
13	Royce Fund:Value Fund	12/31/1983	5/31/1997	162	1.02	0.88	147.95
14	MassMutual Select Funds: MassMutual Select Focused Value Fund	1/31/2001	10/31/2017	202	1.00	0.92	670.02
15	Virtus Asset Trust: Virtus Ceredex Small-Cap Value Equity Fund	6/30/2000	12/31/2018	223	0.99	0.88	847.46
16	Advantage Funds, Inc: Dreyfus Small Company Value Fund	1/31/1994	1/31/2010	193	0.99	0.89	182.08
17	Third Avenue Trust: Third Avenue Value Fund	12/31/1992	6/30/2011	223	0.97	0.87	3462.01
18	Delaware Group Equity Funds V: Delaware Small Cap Value Fund	12/31/1988	12/31/2018	361	0.97	0.84	879.15
19	Advantage Funds, Inc: Dreyfus Opportunistic Midcap Value Fund	12/31/1995	12/31/2018	277	0.97	0.87	1044.75
20	Eaton Vance Mutual Funds Trust: Eaton Vance Tax-Managed Small-Cap Value Fund	10/31/2002	6/30/2015	153	0.97	0.81	31.53

Table 11 : Explaining the Performance of Active Value Funds with the q-factor and q^5 Models

"All, ew" and "All, vw" are the equal- and value- or TNA-weighted portfolios of all active value funds, respectively. The sample is from January 1986 to December 2018. Fund 1, 2, ..., 20 are the top 20 active value funds listed in Table 10, with different sample periods. "Top-20, ew" and "Top-20, vw" are the equal- and value- or TNA-weighted portfolios of the top 20 active value funds from December 1980 to December 2018. For each month, we use all available top 20 funds to form the top-20 portfolios. For each fund or fund portfolio, we report the average fund excess return (Mean), CAPM alpha (α), q-factor alpha (α_q), q^5 alpha (α_{q^5}), q^5 factor 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, as well as R^2. The t-values in the rows beneath the corresponding estimates are adjusted for heteroscedasticity and autocorrelations.

Panel A: Explaining gross fund returns										
Funds	Mean	α	α_q	α_{q^5}	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}	R^2
All, ew	0.67	0.06	−0.10	−0.09	0.97	0.20	0.32	0.09	−0.02	0.95
	2.93	0.74	−1.68	−1.62	50.10	3.29	6.52	2.21	−0.50	
All, vw	0.63	0.01	−0.11	−0.08	0.99	0.12	0.28	0.05	−0.04	0.96
	2.74	0.12	−2.05	−1.73	59.13	2.65	7.09	1.52	−1.13	
Top-20, ew	0.95	0.41	0.27	0.29	0.89	0.42	0.31	0.00	−0.03	0.91
	4.28	3.71	3.60	3.96	31.72	5.25	5.52	−0.01	−0.61	
Top-20, vw	0.86	0.32	0.17	0.19	0.89	0.37	0.28	0.03	−0.02	0.91
	3.92	3.19	2.48	2.74	33.82	5.70	4.87	0.60	−0.54	
1	1.32	0.21	0.25	0.23	0.95	0.08	−0.26	0.20	0.02	0.82
	3.80	1.21	1.01	0.87	15.49	0.93	−1.75	1.81	0.16	
2	1.02	0.63	0.23	0.33	0.82	0.28	0.41	0.08	−0.17	0.83
	2.55	2.91	1.21	1.81	14.44	3.16	4.73	1.11	−1.64	
3	1.10	0.58	0.26	0.16	0.89	0.44	0.25	0.13	0.16	0.83
	3.30	3.01	2.11	1.31	25.75	8.13	3.56	1.77	1.97	
4	0.84	0.41	0.00	0.00	0.87	0.01	0.46	0.19	0.00	0.77
	3.82	3.14	−0.01	−0.03	22.81	0.10	5.12	2.83	0.06	
5	1.25	0.23	0.29	0.36	0.91	−0.03	0.16	0.08	−0.14	0.84
	3.50	1.76	2.17	2.56	15.23	−0.39	1.27	0.95	−1.15	
6	1.03	0.43	−0.08	−0.02	1.11	0.60	0.20	0.17	−0.08	0.91
	2.09	1.78	−0.45	−0.10	19.52	11.86	2.02	1.91	−0.94	
7	1.09	0.20	0.23	0.30	0.95	0.75	−0.49	−0.08	−0.19	0.94
	2.21	0.95	1.91	2.59	22.40	14.70	−5.98	−1.45	−2.05	
8	1.02	0.71	0.38	0.42	0.84	0.42	0.50	−0.25	−0.07	0.79
	2.13	2.67	1.45	1.51	9.48	2.68	3.01	−2.01	−0.58	
9	0.92	0.35	0.06	0.09	0.83	0.59	0.44	0.12	−0.04	0.88
	3.62	2.17	0.64	0.94	25.37	7.98	6.69	2.32	−0.79	
10	1.04	0.53	0.35	0.33	0.96	0.59	0.30	0.00	0.04	0.82
	2.55	2.14	1.92	1.80	11.95	4.17	2.85	−0.05	0.45	
11	1.05	0.63	0.31	0.30	0.99	0.52	0.58	0.02	0.02	0.82
	2.74	2.56	1.69	1.70	12.75	3.28	4.82	0.21	0.18	
12	0.95	0.81	0.28	0.30	0.96	0.30	0.58	0.17	−0.02	0.82
	2.08	3.28	1.39	1.49	13.27	2.45	6.55	2.08	−0.23	
13	0.60	0.01	0.26	0.34	0.70	0.55	0.10	−0.14	−0.12	0.93
	2.00	0.10	2.86	3.58	34.60	14.00	1.87	−3.74	−2.45	
14	1.03	0.44	0.44	0.39	1.05	0.18	0.25	−0.21	0.13	0.87
	2.62	2.52	2.96	2.65	19.73	2.88	2.63	−2.51	1.18	
15	0.98	0.58	0.23	0.22	0.89	0.66	0.34	0.15	0.03	0.87
	3.02	2.98	1.91	1.71	20.45	10.98	4.50	2.43	0.42	
16	0.97	0.45	0.45	0.58	1.09	0.46	0.27	−0.34	−0.17	0.75
	1.70	1.25	1.25	1.49	9.17	2.37	1.55	−1.76	−1.08	
17	0.82	0.36	0.19	0.05	0.90	0.24	0.19	−0.09	0.20	0.77
	2.34	1.95	1.15	0.27	18.28	4.31	2.20	−1.01	2.20	
18	0.84	0.23	−0.10	−0.06	1.00	0.40	0.53	0.22	−0.06	0.82
	3.19	1.44	−0.80	−0.52	22.30	3.46	6.26	3.11	−0.83	
19	0.98	0.24	0.26	0.31	1.20	0.11	0.27	−0.13	−0.08	0.79
	2.50	1.07	1.09	1.25	13.54	0.74	2.15	−0.85	−0.74	
20	0.95	0.17	0.10	0.06	0.84	0.62	0.10	0.11	0.14	0.92
	2.61	1.24	0.91	0.56	22.70	12.63	1.16	1.92	1.42	

Panel B: Explaining net fund returns										
Funds	Mean	α	α_q	α_{q^5}	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}	R^2
All, ew	0.58	−0.03	−0.19	−0.18	0.98	0.20	0.32	0.09	−0.02	0.95
	2.52	−0.34	−3.29	−3.39	50.44	3.30	6.49	2.20	−0.52	
All, vw	0.55	−0.08	−0.19	−0.17	1.00	0.12	0.28	0.05	−0.04	0.96
	2.36	−1.18	−3.74	−3.53	60.29	2.75	7.10	1.50	−1.16	
Top-20, ew	0.83	0.29	0.15	0.16	0.89	0.42	0.31	0.00	−0.03	0.91
	3.73	2.59	1.93	2.25	31.64	5.25	5.51	0.00	−0.62	
Top-20, vw	0.74	0.20	0.06	0.08	0.89	0.37	0.28	0.03	−0.03	0.91
	3.41	2.05	0.89	1.15	33.72	5.69	4.82	0.59	−0.60	
1	1.20	0.09	0.13	0.11	0.95	0.08	−0.26	0.20	0.02	0.82
	3.46	0.54	0.52	0.43	15.47	0.93	−1.74	1.83	0.13	
2	0.87	0.48	0.07	0.18	0.82	0.28	0.41	0.08	−0.17	0.83
	2.15	2.18	0.37	0.96	14.43	3.16	4.73	1.11	−1.64	
3	0.98	0.46	0.14	0.04	0.88	0.44	0.25	0.12	0.16	0.83
	2.93	2.36	1.11	0.32	25.59	8.14	3.57	1.76	1.88	
4	0.69	0.26	−0.15	−0.15	0.87	0.01	0.46	0.19	0.00	0.77
	3.13	1.98	−1.15	−1.14	22.66	0.10	5.11	2.82	0.04	
5	1.21	0.14	0.19	0.22	0.97	0.01	0.24	0.13	−0.07	0.88
	3.30	1.04	1.38	1.59	23.85	0.12	2.10	1.80	−0.62	
6	0.92	0.32	−0.18	−0.13	1.11	0.60	0.20	0.17	−0.08	0.91
	1.87	1.33	−1.09	−0.71	19.54	11.87	2.02	1.91	−0.94	
7	0.98	0.08	0.12	0.19	0.95	0.75	−0.49	−0.08	−0.19	0.94
	1.98	0.41	0.99	1.61	22.42	14.71	−5.99	−1.45	−2.05	
8	0.89	0.58	0.25	0.28	0.84	0.42	0.50	−0.25	−0.07	0.79
	1.84	2.16	0.94	1.03	9.48	2.67	3.01	−2.03	−0.59	
9	0.85	0.28	−0.01	0.02	0.83	0.59	0.44	0.12	−0.05	0.88
	3.33	1.72	−0.10	0.21	25.38	7.96	6.68	2.32	−0.82	
10	0.90	0.39	0.21	0.19	0.96	0.59	0.30	0.00	0.04	0.82
	2.21	1.58	1.16	1.04	11.97	4.16	2.83	−0.04	0.44	
11	0.93	0.50	0.18	0.17	0.99	0.52	0.58	0.02	0.02	0.82
	2.41	2.05	1.00	0.98	12.77	3.28	4.81	0.21	0.19	
12	0.81	0.68	0.15	0.16	0.95	0.30	0.58	0.17	−0.03	0.82
	1.78	2.73	0.72	0.81	13.29	2.44	6.54	2.08	−0.25	
13	0.45	−0.13	0.11	0.20	0.69	0.55	0.10	−0.14	−0.12	0.93
	1.51	−0.95	1.25	2.07	34.46	13.95	1.85	−3.69	−2.44	
14	0.95	0.35	0.35	0.30	1.06	0.18	0.25	−0.19	0.12	0.87
	2.41	2.03	2.34	2.05	19.28	2.92	2.63	−2.26	1.10	
15	0.88	0.48	0.13	0.11	0.89	0.66	0.34	0.15	0.03	0.87
	2.69	2.44	1.05	0.88	20.46	10.98	4.50	2.43	0.41	
16	0.88	0.35	0.36	0.48	1.09	0.46	0.27	−0.33	−0.17	0.75
	1.54	0.98	0.99	1.24	9.19	2.37	1.55	−1.75	−1.07	
17	0.72	0.27	0.09	−0.05	0.90	0.24	0.19	−0.09	0.20	0.77
	2.05	1.42	0.56	−0.28	18.29	4.32	2.19	−1.00	2.19	
18	0.72	0.11	−0.23	−0.19	1.00	0.40	0.52	0.22	−0.06	0.82
	2.72	0.67	−1.79	−1.56	22.44	3.46	6.24	3.13	−0.79	
19	0.89	0.14	0.16	0.21	1.20	0.11	0.27	−0.13	−0.08	0.79
	2.25	0.63	0.67	0.85	13.55	0.74	2.15	−0.85	−0.74	
20	0.80	0.02	−0.06	−0.10	0.85	0.62	0.11	0.11	0.14	0.92
	2.19	0.12	−0.49	−1.04	23.00	12.52	1.26	2.05	1.47	