Security Analysis: An Investment Perspective

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Abstract

The investment theory, in which expected returns vary cross-sectionally with investment, profitability, and expected growth, provides an economic foundation for Graham and Dodd (1934). The q^5 model goes a long way in explaining the performance of top-notch active, discretionary value funds as well as prominent quantitative security analysis strategies, such as Abarbanell and Bushee's (1998) fundamental signals, Frankel and Lee's (1998) intrinsic-to-market, 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, Ball, Gerakos, Linnainmaa, and Nikolaev's (2020) retained earnings-to-market, Penman and Zhu's (2014, 2020) expected-return strategy, and Penman and Zhang's (2020a) accounting-based factors.

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1 Introduction

Graham and Dodd (1934, 1940) pioneer an investment philosophy that buys undervalued securities selling below their intrinsic values. Their teachings have had 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. Unfortunately, perhaps because it is premised on the discrepancy between the intrinsic value and the market value of an asset, security analysis has long been perceived as incompatible with modern finance, the bulk of which builds on efficient markets (Fama 1970). This perspective pervades the contemporary literature in accounting and finance (Frankel and Lee 1998; Piotroski 2000; Bartram and Grinblatt 2018).

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

As the theory's empirical implementation, the q^5 model goes a long way in explaining best-performing active, discretionary value funds, which exploit hard-to-quantify, qualitative information. From January 1986 to December 2020, net of fees, the aggregate equal- and total net assets (TNA)-weighted portfolios of active value funds in the CRSP Mutual Fund database roughly breaks even with the market portfolio but underperform the q^5 model by 9–26 basis points per month.

Most important, for portfolios consisting of *only* top-20 active value funds, the q^5 model explains

67–84% of their performance, depending on specific measurement. The equal-weighted top-20 fund portfolio earns an average excess return before fees of 1% per month (t = 4.52). The q^5 model shrinks it to an alpha of 0.33% (t = 4.9), which represents a reduction of 67% in magnitude. For the TNA-weighted top-20 fund portfolio, the q^5 model reduces the average excess return of 0.9% (t = 4.22) to an alpha of 0.24% (t = 3.68), yielding a reduction of 73% in magnitude. Net of fees, the equal-weighted top-20 fund portfolio earns 0.88% (t = 3.97), and the q^5 model shrinks the average return by 76% to an alpha of 0.21% (t = 3.11). Finally, the TNA-weighted top-20 fund portfolio earns 0.79% (t = 3.7), net of fees, but the q^5 alpha is only 0.13% (t = 2.01), which represents a reduction of 84% in magnitude. Across the top-20 funds, the market, size, and investment factor loadings are mostly positive, large, and significant. The Roe factor loadings are mostly insignificant, with mixed signs, and the expected growth factor loadings are mostly negative but insignificant.

In addition, the q^5 model largely explains prominent quantitative strategies grounded in security analysis. The model largely explains Abarbanell and Bushee's (1998) fundamental strategy, which combines a collection of 7 signals. From January 1967 to December 2020, the high-minus-low decile formed on their composite score earns on average 0.29% per month (t = 2.42), but its q^5 alpha is only 0.13% (t = 0.85). The key driving force is a large Roe factor loading, 0.26 (t = 2.93).

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

Piotroski's (2000) fundamental score combines 9 signals on profitability, liquidity, and operating efficiency. The return on equity (Roe) factor largely explains his anomaly. The high-minus-low quintile earns 0.36%, 0.3%, and 0.2% per month (t = 2.21, 2.08, and 1.31) across micro, small, and big stocks, and the q^5 alphas are 0.28%, 0.14%, and 0.04% ($t = 2.19$, 1.04, and 0.22), helped by the large Roe factor loadings of 0.62, 0.47, and 0.4 ($t = 6.37$, 5.68, and 3.98), respectively.

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. The high-minus-low quintile earns 0.35%, 0.4%, and 0.41% per month ($t = 2.05$, 2.49, and 2.7) across micro, small, and big stocks, and the q^5 alphas are 0.06%, 0.04%, and −0.13% ($t = 0.46$, 0.29, and −0.98), helped by the large Roe factor loadings of 0.67, 0.59, and 0.42 ($t = 6.22$, 5.3, and 4.85), respectively.

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

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

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 0.5%, 0.38%, and 0.29% per month ($t = 2.45$, 2.01, and 1.6) across micro, small, and big stocks, and the q^5 alphas are 0.17%, −0.04%, and −0.35% ($t = 0.98$, −0.31, and −2.23), respectively. Arising again from the investment-value linkage, the investment factor loadings are large and significant. Moreover, motivated by Ball (1978) and Ball, Gerakos, Linnainmaa, and Nikolaev (2016), we document that operating cash flow-to-market is a very strong predictor of returns. The high-minus-low quintile earns on average 0.88%, 0.61%, and 0.37% ($t = 6.22, 3.75$, and 1.99) in micro, small, and big stocks, and the q^5 alphas are 0.51%, 0.12%, and −0.03% ($t = 3.72, 0.85$, and −0.22), respectively.

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

Penman and Zhang (2020a, b) challenge the accounting treatment underlying the q models. We clarify that our treatment is largely congruent with their view of accounting. First, the q^5 model handles tangible and intangible investments differently, with the former via the investment factor and the latter via the expected growth factor. This treatment accommodates their differential risks that arise from conservative accounting. Second, Penman and Zhang document a weakly negative relation between annual return on equity (Roe) and expected returns and interpret this evidence as contradicting the investment theory. We show that the weakly negative Roe-return relation resides only in annual sorts. In monthly sorts on quarterly Roe, the positive Roe-return relation postulated in the investment theory dominates the negative relation from conservative accounting. In addition, because of information advantage of quarterly earnings announcements, quarterly Roe outperforms other quarterly profitability measures in monthly sorts.

Finally, in head-to-head factor spanning tests, the q^5 model fully subsumes the Penman-Zhang (2020a) 3-factor model, but the converse is not true. Their "grand" factor that summarizes salient accounting features earns on average 0.52% per month ($t = 2.57$), but the q^5 alpha is insignificant, 0.2% ($t = 1.09$). Conversely, their 3-factor alphas of our investment, Roe, and expected growth factors are highly significant, 0.27%, 0.65%, and 0.93% ($t = 4.45$, 7.37, and 13.58), respectively.

Our contribution is to validate Graham and Dodd (1934) within efficient markets. On the one hand, Graham and Dodd attribute return predictability with accounting variables entirely to mispricing. By connecting expected returns to accounting variables, but without expectation errors, the investment theory shows that security analysis *should* work within efficient markets to begin with. After all, the investment theory is mathematically equivalent to the *un*controversial net present value rule in corporate finance. On the other hand, academic finance, with the classic 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 2021). Instead of the first principle of investors, we study expected returns via the first principle of issuers. By inheriting Graham and Dodd's primary focus on firms, we validate security analysis on equilibrium grounds.

To our knowledge, Ball (1978) is the first to argue that accounting information is connected with expected returns, especially when scaled by price.[1] Ball and Brown (1968) and Ball, Gerakos, Linnainmaa, and Nikolaev (2015, 2016, 2020) test these insights with different measures of earnings yields. We show, systematically, how the linkage between accounting variables and expected returns arises endogenously in an optimized equilibrium prescribed by the investment theory, while prior studies do not establish such an equilibrium perspective. Empirically, we also detail how the q^5 model adequately explains active value funds and quantitative security analysis strategies.

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

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

to expected earnings growth (as well as risks and expected returns) via accounting conservatism (Penman, Reggiani, Richardson, and Tuna 2018).[2] By comparison, the tight, economic linkage between investment and the market equity allows us to substitute, mathematically, expected capital gain with expected investment growth. In this sense, the investment theory is perhaps even more "fundamental" than the Penman-Zhu model, which still has the market equity in its formulation.[3]

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 active value funds in Section 3 and quantitative strategies grounded in security analysis in Section 4. We conclude in Section 5. A separate Internet Appendix details measurement and supplementary results.

2 An Economic Perspective on Security Analysis

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

2.1 The Graham-Dodd Perspective

Graham and Dodd (1934, 1940) lay the intellectual foundation for security analysis, which is "concerned with the intrinsic value of the security and more particularly with the discovery of discrepancies between the intrinsic value and the market price (p. 20)."[4] The basic philosophy is to invest in undervalued securities that are selling well below the intrinsic value, "which is justified by the facts, e.g., the assets, earnings, dividends, definite prospects, as distinct, let us say, from market

[2]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 (2020) 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.

[3]Hou, Xue, and Zhang (2015) construct the q-factor model, and Hou, Mo, Xue, and Zhang (2021) add expected growth to form the q^5 model. We bring the investment theory to bear with the illustrious fundamental analysis literature in accounting. Conceptually, we show how financial statement analysis originated from Graham and Dodd (1934) can be reconciled with modern finance via cross-sectionally varying expected returns. Empirically, we document that the q^5 model goes a long way in explaining active, discretionary value funds and prominent security analysis strategies.

[4]Our references to specific page numbers are from Graham and Dodd (1940), the second edition, which is viewed as more authoritative, see Warren Buffett's discussion at `https://www.youtube.com/watch?v=AZFFKF3OY9I`.

quotations established by artificial manipulation or distorted by psychological excesses (p. 20–21)." However, the intrinsic value is not exactly defined: "[S]ecurity analysis does not seek to determine exactly what is the intrinsic value of a given security. It needs only to establish either that the value is *adequate*—e.g., to protect a bond or to justify a stock purchase—or else that the value is considerably higher or considerably lower than the market price (p. 22, original emphasis)."

Graham and Dodd (1940) clearly perceive 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 accounting and finance literatures offer contradictory 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) states: "Passive investors accept market prices as fair value. Fundamental investors, in contrast, are active investors. They see that *price is what you pay, value is what you get*. They understand that *the primary risk in investing is the risk of paying too much* (or selling for too little). The fundamentalist actively challenges the market price: Is it indeed a fair price (p. 210, original emphasis)?"

On the other hand, the traditional view of academic finance, with the classic Sharpe-Lintner CAPM as the workhorse theory of efficient markets, tends to dismiss any profits from security analysis as purely from luck and recommend investors to passively hold the market portfolio. 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 negative view has mostly persisted today. In a leading textbook on investments, Bodie, Kane, and Marcus (2021) 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. 339, original emphasis)." In a Bloomberg interview on November 5, 2019, Fama even labels equity research on Wall Street as "business-related pornography."

2.3 Our Economic Perspective

Because realized returns equal expected returns plus abnormal returns, predictability with any anomaly variables has two parallel interpretations. In the first, the variables forecast abnormal returns, or forecasting errors are forecastable, violating efficient markets (Graham and Dodd 1934, 1940).[5] In the second, the variables are connected, cross-sectionally, to expected returns, but abnormal returns are unpredictable, thereby retaining efficient markets (Ball 1978; Zhang 2017).

2.3.1 The First Principle

The investment theory details how the expected return is connected with anomaly variables in the cross section. The first principle of real investment implies that:

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

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

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) reduces to $r_{t+1} = (X_{t+1} + 1 - \delta)/(1 + aI_t/A_t)$. All else equal, low investment and high profitability stocks should earn higher expected returns than high investment and low profitability stocks, respectively (Hou, Xue, and Zhang 2015). In a multiperiod model, high expected investment relative to current investment must imply high discount rates to offset the high

[5] 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).

expected marginal benefit of current investment to keep current investment low (Hou et al. 2021).

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 that of 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 Foundation for 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.

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

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

Clearly, one needs both demand and supply to fully grasp equilibrium asset pricing. Betas play a central role in the CAPM and its extensions, which do not model accounting variables. Symmetrically, accounting variables play a central role in the investment theory, which does not model betas. As such, we view the investment theory primarily as an expected-return model that can potentially yield more reliable expected-return estimates (to aid, for example, portfolio optimization) than traditional asset pricing models. While the CAPM 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 (supply-focused) security analysis has long been perceived as diametrically opposite to (mostly demand-focused) modern finance. In particular, honoring the 50th anniversary of Graham and Dodd (1934), Buffett (1984) reports the successful performance of 9 famous value investors. After arguing that their success is beyond chance, Buffett writes: "Our Graham & Dodd investors, needless to say, do not discuss beta, the capital asset pricing model or covariance in returns among securities. These are not subjects of any interest to them. In fact, most of them would have difficulty defining those terms (p. 7)." This dichotomy is unfortunate, as demand and supply are the two sides of the same coin of equilibrium asset pricing.

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)." However, precisely because investors are left unmodeled, we have little to say about the expected growth risk. While our perspective on security analysis accords with efficient markets by connecting accounting information to expected returns à la Ball (1978), we emphasize that our evidence does not rule out distorted beliefs on the investor side. Rather, challenging the conventional wisdom that security analysis only works in inefficient markets, we show that security analysis should work in efficient markets to begin with.

3 Explaining the Performance of Active Value Funds

Quantitative strategies select stocks based on potentially distorted accounting numbers and overlook important, qualitative information that active, discretionary managers exploit. To mitigate this concern, we start our empirical analysis with best-performing active value funds in Section 3.1 and Buffett's Berkshire Hathaway in Section 3.2. These active value funds are discretionary, going beyond algorithmic rules. We use the q-factor and q^5 models to explain the performance of active value funds. The factors data are from the q-factor data library (`http://global-q.org`).

3.1 Best-performing Active Value 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 that contain the exact word "value" (Lettau, Ludvigson, and Manoel 2019).[6] 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.[7] 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). To compute gross fund returns, we require non-missing net fund returns but impute a given missing monthly expense ratio with its latest value in the past 12 months (if available). Our aggregate portfolio of domestic active value funds covers 880 unique funds from January 1986 to December 2020. We start in 1986 to have at least 10 funds in each month.

[6] 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.

[7] 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."

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 402 unique value funds with an uninterrupted track record of at least 10 years. 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, such hindsight bias goes against our models in explaining their performance.

Table 1 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 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 $1,884.3 million. This TNA is relatively large. Among the 402 active value funds with an uninterrupted record of at least 10 years, the mean TNA is $976.2 million, and median $346.2 million. The best fund's TNA resides between the 75th percentile, $1,058.2 million, and the 90th percentile, $2,380.8 million.

The largest top-20 fund is T. Rowe Price Small-Cap Value Fund, with an average TNA of $4,658.1 million, which is larger than the 95th percentile of $4,114.5 million. Its monthly geometric average gross return of 1.07% from December 1990 to December 2020 ranks 8th on the top-20 list. Finally, the smallest fund on the list is Guggenheim Funds Trust: Guggenheim Small Cap Value Fund, with only a TNA of $20.4 million, which is smaller than the 5th percentile of $25.4 million. Its average gross return of 1% from October 2008 to December 2020 ranks 17th on the list.

Panel A of Table 2 shows that the aggregate equal-weighted portfolio of all active value funds earns an average gross return (in excess of the riskfree rate) of 0.78% per month ($t = 3.43$). However, consistent with Sharpe's (1991) arithmetic of active management, the CAPM alpha is only 0.09% ($t = 0.77$). As such, the average fund barely beats the market before fees. The q^5 alpha is tiny, 0.01% ($t = 0.13$). 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 weakly negative. The time series R^2 is 0.89. The TNA-wighted aggregate portfolio earns on average 0.75% ($t = 3.2$). The CAPM alpha is again only weakly positive, 0.07% ($t = 0.46$). However, the q^5 alpha becomes weakly negative, -0.17% ($t = -1.63$), indicating a small amount of underperformance. The market, size, and investment factor loadings continue to be large and significant, but the Roe and expected growth loadings are small and insignificant.

From Panel B, net of fees, the equal-weighted aggregate fund portfolio earns on average 0.69% per month ($t = 3$), with a tiny negative CAPM alpha of -0.01%. This portfolio underperforms the q^5 model with a negative alpha of -0.09%, albeit insignificant ($t = -1.05$). The TNA-weighted aggregate portfolio, net of fees, earns on average 0.66% ($t = 2.83$), also with a tiny CAPM alpha of -0.02%. The portfolio significantly underperforms the q^5 model with an alpha of -0.26% ($t = -2.45$). Both equal- and TNA-weighted portfolios have large and significant market, size, and investment factor loadings but small and mostly insignificant Roe and expected growth loadings.

The top-20 funds represent a very high hurdle for the q^5 model. From Panel A, the equal-weighted top-20 fund portfolio earns an average excess return before fees of 1% per month ($t = 4.52$), which yields a CAPM alpha of 0.38% ($t = 3.32$). The q^5 model shrinks the average return to an alpha of 0.33%, which represents a reduction of 67% in magnitude, although the alpha remains significant ($t = 4.9$). The market, size, and investment factor loadings are all large and significant, whereas the Roe and expected growth factor loadings are close to zero. For the TNA-weighted top-20 fund portfolio, the q^5 model reduces the average excess return, 0.9% ($t = 4.22$), to an alpha of 0.24% ($t = 3.68$), which yields a reduction of 73% in magnitude. The market, size, and investment factor loadings continue to be large and significant, the Roe loading remains tiny, but the expected growth factor loading becomes significantly negative, -0.13 ($t = -2.13$).

Panel B shows that, net of fees, the equal-weighted top-20 fund portfolio earns on average 0.88% ($t = 3.97$). The q^5 model yields an alpha of 0.21% ($t = 3.11$), a reduction of 76% in magnitude from the average excess return. For the TNA-weighted top-20 fund portfolio, its average excess return is 0.79% ($t = 3.7$), but the q^5 alpha is only 0.13% ($t = 2.01$), which represents a reduction of 84% in magnitude. The factor loadings follow similar patterns as those of gross fund returns.

The remainder of Table 2 shows the q^5 regression for each of the top-20 funds. From Panel A, the average excess returns before fees range from 0.6% ($t = 1.99$) to 1.32% per month ($t = 3.78$) across the top-20 funds.[8] The q^5 alphas vary from 0.0% ($t = 0.02$) to 0.61% ($t = 1.55$). Only 8 out of 20 q^5 alphas are significant at the 5% level. Panel B shows that net of fees, the average excess returns range from 0.45% ($t = 1.51$) to 1.2% ($t = 3.45$). The q^5 alphas vary from -0.15% ($t = -1.08$) to 0.51% ($t = 1.3$), and only 1 out of 20 q^5 alphas is significant at the 5% level.

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. From Panel A, for the q^5 regressions with gross returns, all 20 market betas, 15 size factor loadings, and 14 investment factor loadings are significantly positive. Interestingly, three funds have negative investment factor loadings: Morgan Stanley Dean Witter American Value, -0.23 ($t = -1.53$); Wasatch Micro Cap Value Fund, -0.51 ($t = -5.31$); and Royce Value Plus Fund, -0.58 ($t = -6.5$). The evidence suggests that these funds might not be value funds as advertised. Across the top 20 funds, the Roe factor loadings are mostly insignificant, with mixed signs. The expected growth loadings are mostly negative but insignificant. From Panel B, the evidence from net return regressions is largely similar.

3.2 Buffett's Alpha

We obtain Berkshire's return and price data first from CRSP and then fill in missing observations using data from Compustat. The sample constructed in this way goes from February 1968 to December 2020. The observations prior to November 1976, in January and February 1977, in March and April 1978, and in May and June 1979 are from Compustat, and the remainder from CRSP.[9]

[8] The average excess returns in Table 2 are simple returns, which are appropriate for factor regressions. These returns differ from the geometric average raw returns in Table 1 used to rank the full-life performance of funds.

[9] 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.

In the 1968–2020 sample, Berkshire's excess return is on average 1.41% per month ($t = 4.98$). The q-factor model reduces the average return by 58% to an alpha of 0.59%, albeit still significant ($t = 2.34$), aided by large investment and Roe factor loadings of 0.59 ($t = 3.82$) and 0.38 ($t = 3.31$), respectively. The evidence indicates that Berkshire behaves like high profitability and low investment stocks. Because the investment factor is a substitute for the value factor in the q-factor model, the evidence echoes Buffett's well known philosophy of buying profitable firms at bargain prices.

The expected growth factor loading in the q^5 regression is -0.23, albeit insignificant ($t = -1.3$), going in the wrong direction as the average return to yield a higher q^5 alpha of 0.74% ($t = 2.66$). The evidence is corroborated by Buffett's reluctance in investing high expected growth stocks, likely because of their relatively high valuation (and uncertainty with future growth). We emphasize that the q^5 model features two related but different aspects of quality, expected profitability and expected growth. 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.

Frazzini, Kabiller, and Pedersen (2018) show that Buffett's alpha 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 3 largely reproduces their evidence. We obtain an AQR 6-factor alpha of 0.45% ($t = 1.67$) in the same sample period. Our loadings are also close to their original estimates. However, once we extend the sample backward to February 1968 (and forward to December 2020), the AQR 6-factor alpha rises to 0.58% ($t = 2.07$). Finally, the q-factor alphas are close to the AQR alphas across the two samples, but the q^5 alphas are somewhat larger due to the negative expected growth loadings.[10]

[10] Prior to September 1988, monthly Berkshire returns can differ drastically between CRSP and Compustat. The deviations vary from -25.2% to $+20.3\%$, with an average magnitude of 0.36%. From September 1988 onward, the returns from the two sources are exactly identical. For robustness, we have also examined the evidence with Compustat's Berkshire returns prior to September 1988. The results are quantitatively close (the Internet Appendix, Table S1).

4 Explaining Quantitative Security Analysis Strategies

The academic literature in accounting and finance has most implemented security analysis quantitatively. We use the q models to explain prominent security analysis strategies: Abarbanell and Bushee's (1998) fundamental strategy (Section 4.1), Frankel and Lee's (1998) intrinsic-to-market value (Section 4.2), Piotroski's (2000) fundamental score (Section 4.3), Greenblatt's (2005, 2010) "magic formula" (Section 4.4), Asness, Frazzini, and Pedersen's (2019) quality-minus-junk (Section 4.5), Bartram and Grinblatt's (2018) agnostic strategy (Section 4.6), Ball, Gerakos, Linnainmaa, and Nikolaev's (2020) retained earnings (Section 4.7), Penman and Zhu's (2014, 2020) expected returns (Section 4.8), and Penman and Zhang's (2020) accounting-based factors (Section 4.9).

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 2020.

4.1 Abarbanell and Bushee's (1998) Fundamental Strategy

Abarbanell and Bushee (1998) show that a collection of fundamental signals, which contain information about future earnings news, can forecast returns. Their collection includes inventory, account receivable, capital expenditure, gross margin, selling and administrative expenses, effective tax rate, and labor force efficiency.[11] We use the 7 signals to form a composite signal, denoted AB,

[11] Following Abarbanell and Bushee (1998), we define the %d(·) operator as the percentage change in the variable in the parentheses from its average over the prior two years, for example, %d(Sales) = [Sales(t) − E[Sales(t)]]/E[Sales(t)], in which E[Sales(t)] = [Sales($t-1$) + Sales($t-2$)]/2. Inventory is calculated as %d(Sales) − %d(Inv), in which sales is net sales (Compustat annual item SALE), and inv is finished goods inventories (item INVFG) if available, or total inventories (item INVT). Firms with nonpositive average sales or inventory during the past two years are excluded. Account receivable is %d(Sales) − %d(RECT), in which RECT is total receivables (item RECT). Firms with nonpositive average sales or receivables during the past two years are excluded. Capital expenditure is %d(Investment) − %d(Industry investment), in which investment is capital expenditure in property, plant, and equipment (item CAPXV). Industry investment is the aggregate investment across all firms with the same 2-digit SIC code. Firms with nonpositive E[Investment(t)] are excluded and we require at least two firms in each industry. Gross margin is %d(Gross margin) − %d(Sales), in which gross margin is sales minus cost of goods sold (item COGS). Firms with nonpositive average gross margin or sales during the past two years are excluded. Selling and administrative expenses are %d(Sales) − %d(SG&A), in which SG&A is item XSGA. Firms with nonpositive average sales or SG&A during the past two years are excluded. Effective tax rate is $\left[\frac{\text{TaxExpense}(t)}{\text{EBT}(t)} - \frac{1}{3}\sum_{\tau=1}^{3}\frac{\text{TaxExpense}(t-\tau)}{\text{EBT}(t-\tau)}\right] \times \text{dEPS}(t)$, in which TaxExpense($t$) is total income taxes (item TXT) paid in year t, EBT(t) is pretax income (item PI) plus amortization of intangibles (item AM), and dEPS is the change in split-adjusted earnings per share (item EPSPX divided by item AJEX) between years $t-1$ and t, deflated by stock price (item PRCC_F) at the end of $t-1$. Finally, labor force efficiency for year t is

which equal-weights a stock's percentile rankings of the signals (each realigned to yield a positive slope when forecasting returns). At the end of June of each year t, we sort stocks into deciles based on the NYSE breakpoints of AB for the fiscal year ending in calendar year $t-1$. Monthly value-weighted decile returns are from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. We also perform double 3×5 sorts on size and AB. At the end of June of year t, we sort stocks into quintiles based on the NYSE breakpoints of AB for the fiscal year ending in year $t-1$, and independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the market equity at the June-end of t. Taking intersections yields 15 portfolios.

Table 4 shows that consistent with Abarbanell and Bushee (1998), their composite signal, AB, reliably predicts returns. From Panel A, the high-minus-low decile earns on average 0.29% per month ($t = 2.42$). Both the q and q^5 models leave insignificant high-minus-low alphas. In the q^5 regression, the Roe factor loading is 0.26 ($t = 2.93$), the size loading is 0.13 ($t = 2.44$), but the other loadings are insignificant. The Gibbons-Ross-Shanken (1989, GRS) test on the null that the alphas are jointly zero across the deciles fails to reject either q or q^5 model.

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

$\left[\frac{\text{Sales}(t)}{\text{Employees}(t)} - \frac{\text{Sales}(t-1)}{\text{Employees}(t-1)}\right] / \frac{\text{Sales}(t-1)}{\text{Employees}(t-1)}$, in which Employees($t$) is the number of employees (item EMP). Abarbanell and Bushee also consider two indicators, earnings quality (1 for LIFO and 0 otherwise) and audit qualification (1 for unqualified and 0 otherwise). We drop the two indicators because they are unfit for forming portfolios.

4.2 Frankel and Lee's (1998) Intrinsic-to-market Strategy

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.[12]

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.

Table 5 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 0.23% per month, albeit insignificant ($t = 1.29$). Its q-factor and q^5 alphas are economically small and statistically insignificant. However, both are rejected by the GRS test on the null that the alphas are jointly zero

[12] B_t is the book equity (Compustat annual item CEQ) for the fiscal year ending in calendar year $t-1$. Future book equity is computed with the clean surplus accounting, $B_{t+1} = (1 + (1-k)E_t[\text{Roe}_{t+1}])B_t$, in which k is the dividend payout ratio, measured as common stock dividends (item DVC) divided by earnings (item IBCOM) for the fiscal year ending in calendar year $t-1$. For firms with negative earnings, we divide dividends by 6% of average total assets (item AT) from the fiscal years ending in calendar years $t-1$ and $t-2$. The discount rate, r, is a constant, 12%. $E_t[\text{Roe}_{t+1}]$ and $E_t[\text{Roe}_{t+2}]$ are replaced with most recent Roe_t, defined as $Ni_t/[(B_t + B_{t-1})/2]$, in which Ni_t is earnings (Compustat annual item IBCOM) for the fiscal year ending in $t-1$, and B_t and B_{t-1} are the book equity from the fiscal years ending in $t-1$ and $t-2$. We exclude firms if their expected Roe or dividend payout ratio is higher than 100%. We also exclude firms with negative book equity and firms with non-positive intrinsic value.

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

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

In the investment theory, 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 theory, should forecast returns. Most important, the book-to-market component of intrinsic-to-market is linked to investment. This linkage arises because the marginal cost of investment, which rises with investment, equals the marginal q, which is the inverse of book-to-market equity (without debt). Although profitability and expected growth (via the book equity at $t + 1$) also appear in equation (2), empirically, the investment factor is the key driving force.

More broadly, even without mispricing, an estimated intrinsic value can deviate from the market value because of errors in cash flow forecasts and in discount rates. Accounting textbooks typically go to great lengths for cash flow forecasts but refer to investment textbooks for discount rates (Penman 2013). However, it is well known that the discount rate estimates from multifactor models are very imprecise, even at the industry level (Fama and French 1997). Unfortunately, intrinsic value estimates can be very sensitive to the assumed discount rates.[13] As such, we view the Frankel-Lee intrinsic value estimates in equation (2), which assumes a constant discount rate of 12%, mostly as a nonlinear function of investment, profitability, and expected growth.

4.3 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 9 fundamental signals to measure a firm's profitability, liquidity, and operating efficiency. Each signal is classified as good or bad (1 or 0), depending on its implications for future stock prices and profitability. The fundamental score, denoted F, is the sum of the 9 binary signals. All the accounting variables in the F-score construction are from Compustat Annual Fundamental Files (the Internet Appendix, Section B.1).

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 7 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 6 shows that the F-score predictability is mixed in our extended sample. The high-minus-low portfolio earns on average only 0.2% per month ($t = 0.8$).[14] The evidence is stronger

[13] For example, Penman (2013) writes: "Compound the error in beta and the error in the risk premium and you have a considerable problem. The CAPM, even if true, is quite imprecise when applied. Let's be honest with ourselves: No one knows what the market risk premium is. And adopting multifactor pricing models adds more risk premiums and betas to estimate. These models contain a strong element of smoke and mirrors (p. 650)."

[14] 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 -0.04% per month ($t = -0.1$). 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 0.73%, albeit still

in quintiles. Across micro, small, and big stocks, the quintile spreads are 0.36%, 0.3%, and 0.2% ($t=$ 2.21, 2.08, and 1.31), respectively. The q-factor and q^5 models largely explain this predictability. The q-factor alphas of the quintile spreads are 0.11%, 0.07%, and 0.07% ($t=0.64$, 0.51, and 0.48), and the q^5 alphas 0.28%, 0.14%, and 0.04% ($t=2.19$, 1.04, and 0.22), respectively. The GRS test cannot reject the q-factor model with the 15 testing portfolios ($p=0.05$) or the q^5 model ($p=0.19$).

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 0.62, 0.47, and 0.4 ($t=6.37$, 5.68, and 3.98) 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.

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, with two values (1 and 0). 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.

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

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

We follow the measurement in Greenblatt (2010, Appendix). Return on capital is earnings be-

insignificant ($t=1.61$). From January 1999 onward, the average return is -0.96% ($t=-1.59$). 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% ($t=1.67$) and -0.17% ($t=-0.41$) before and after December 1998, respectively.

fore 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.[15] 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 7 shows that the Greenblatt measure forecasts returns reliably. The high-minus-low decile earns on average 0.57% per month ($t = 2.54$). In two-way sorts, the high-minus-low quintile earns on average 0.35%, 0.4%, and 0.41% ($t = 2.05$, 2.49, and 2.7) across micro, small, and big stocks, respectively. The q-factor and q^5 models largely explain the Greenblatt formula. The high-minus-low decile has a q-factor alpha of 0.19% ($t = 1.1$) and a q^5 alpha of -0.13% ($t = -0.76$). The high-minus-low quintile has q-factor alphas of 0.0%, 0.03%, and 0.14% ($t = 0.01$, 0.22, and 1.03) and q^5 alphas of 0.06%, 0.04%, and -0.13% ($t = 0.46$, 0.29, and -0.98) across micro, small, and big stocks, respectively. The GRS test cannot reject the q-factor or q^5 model with the two-way portfolios.

The Roe factor is the key driving force behind the explanatory power. In the q^5 regressions of the high-minus-low portfolios, the Roe factor loadings are consistently large and significant in both one-way and two-way sorts. The investment factor loadings are large and significant for micro and small stocks, but not for big stocks. The expected growth factor loadings are significantly

[15] 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.

positive for big stocks but not for micro or small stocks. Intuitively, as a measure of profitability, Greenblatt's (2010) return on capital is closely related to Roe. The earnings yield is a value metric, which connects to investment due to the investment-value linkage.

4.5 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.

Following Asness, Frazzini, and Pedersen (2019), 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 standardized into a z-score. Standardization means dividing the cross-sectionally demeaned values of the rankings by their cross-sectional standard deviation. The profitability score averages the individual z-scores of the six profitability measures. We measure growth as the 5-year growth in residual per-share profitability measures, excluding accruals. The growth score averages the individual z-scores of the 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 averages the individual z-scores of the five safety measures. The Internet Appendix (Section B.2) details the measurement.

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 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 8 shows that the quality-minus-junk decile earns on average 0.28% per month but is only marginally significant ($t = 1.43$).[16] The q-factor model fails to explain this spread, with an alpha of 0.38% ($t = 2.82$), and the model is rejected by the GRS test on the null that the alphas across the quality deciles are jointly zero ($p = 0.00$). More important, the q^5 model yields a tiny alpha of 0.02% ($t = 0.15$), and the GRS test fails to reject the q^5 model ($p = 0.11$). In the q^5 regression, the quality-minus-junk decile has significantly negative market, size, and investment loadings, which go in the wrong way as the average return. Going in the right direction, the quality-minus-junk decile also has significantly positive Roe and expected growth loadings.

Panel B shows that the quality premium varies inversely with size, 0.55%, 0.37%, and 0.22% ($t = 3.61$, 2.88, and 1.51) across micro, small, and big stocks, respectively. The q-factor alphas are all economically large and statistically significant, 0.36%, 0.22%, and 0.31% ($t = 2.91$, 2.05, and 2.62), respectively. Other than the alpha in micro stocks, 0.27% ($t = 2.02$), the q^5 alphas continue to be small, 0.08% ($t = 0.77$) in small stocks and 0.04% ($t = 0.38$) in big stocks. The size and investment factor loadings again go in the wrong direction, especially in big stocks, but the Roe and expected growth factor loadings are sufficiently powerful to yield small q^5 alphas. However, the q^5 model is still rejected by the GRS test across the 15 two-way portfolios ($p = 0.00$).

Asness, Frazzini, and Pedersen (2019) also construct an alternative quality score as the average of the profitability, growth, safety, and payout scores. The payout z-score averages the z-scores

[16] 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% ($t = 2.1$).

based on the rankings of equity net issuance, debt net issuance, and total net payout over profits (the Internet Appendix, Section B.2). Because the quality-minus-junk factor posted on the AQR Web site contains the payout component,[17] we also examine this alternative quality score for robustness.

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

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

The high-minus-low growth decile has positive Roe and expected growth factor loadings of 0.37 and 0.23, respectively. However, the investment factor loading is large, -1.08 ($t = -11.93$). 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 the investment factor. As such, the construction of the Asness-Frazzini-Pedersen (2019) growth score can potentially be improved. Their growth score aims to model expected growth but ends up capturing past growth (investment) more than expected growth.

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

4.6 Bartram and Grinblatt's (2018) Agnostic 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.[18] The sample starts in January 1977 because of the low coverage of the right-hand side accounting variables prior to 1977.

The dependent and explanatory variables in the monthly cross-sectional intrinsic value regressions are contemporaneous. At the beginning of each month, we regress the beginning-of-the-month market equity on the most recently available quarterly accounting variables (from the fiscal quarter ending at least 4 months ago).[19] 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

[18]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.

[19]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.

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

From Panel B, the q models do a good job in the two-way portfolios. The high-minus-low agnostic quintiles earn on average 0.81%, 0.42%, and 0.36% per month ($t = 3.71$, 2.09, and 1.59) across micro, small, and big stocks, respectively. The q-factor model reduces the average returns to insignificance, with alphas of 0.46%, 0.15%, and 0.2% ($t = 1.78$, 0.61, and 0.73), and the q^5 model does too, with alphas of 0.42%, 0.27%, and 0.36% ($t = 1.62$, 1.33, and 1.56), respectively. The investment factor loadings are economically large and highly significant, but the Roe and expected growth factor loadings are mostly insignificant, with mixed signs.[20]

4.7 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

[20] Bartram and Grinblatt (2018) impose the \$5 price screen in their sample selection, but to be consistent with our other tests, we do not. The Internet Appendix furnishes the evidence with the \$5 price screen imposed (Table S7). The results are largely similar. The high-minus-low agnostic decile earns a somewhat higher average return of 0.53% per month ($t = 2.75$), and its q^5 alpha is 0.31% ($t = 1.66$). The high-minus-low quintiles earn on average 0.71%, 0.43%, and 0.28% ($t = 3.15$, 2.1, and 1.24) across micro, small, and big stocks, respectively. The q^5 alpha becomes significant in microcaps but remain relatively small and insignificant in small and big stocks.

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).[21] 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 10, the high-minus-low decile earns on average 0.35% per month ($t = 1.66$). The q and q^5 models both yield small alphas, but are still rejected by the GRS test. In two-way sorts, the high-minus-low quintile earns on average 0.5%, 0.38%, and 0.29% ($t = 2.45, 2.01$, and 1.6), and the q^5 alphas are 0.17%, -0.04%, and -0.35% ($t = 0.98, -0.31$, and -2.23), respectively. The q-factor alphas are all small and insignificant. 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.

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 10, 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 $t-1$).[22]

[21] 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.

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

Table 11 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 0.79% per month (t = 3.73). The q-factor model leaves unexplained a large alpha of 0.5% (t = 2.89). However, the q^5 model largely explains the return spread with a small alpha of 0.15% (t = 0.92), and the model cannot be rejected by the GRS test (p = 0.59). In the two-way sorts, the high-minus-low quintile earns on average 0.88%, 0.61%, and 0.37% ($t = 6.22, 3.75$, and 1.99), and their q^5 alphas are 0.51%, 0.12%, and −0.03% ($t = 3.72, 0.85$, and −0.22), respectively. As such, except for microcaps, the q^5 model largely explains the quintile spreads. The investment factor loadings are economically large and statistically significant. The expected growth factor loadings are positive but insignificant. However, the model is still rejected by the GRS test with the 15 portfolios (p = 0.00).

4.8 Penman and Zhu's (2014, 2020) Expected-return 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, $E_t[r_{it+1}]$, as:

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

The expected change in the market-minus-book equity (the market equity's deviation from the book equity), $E_t[(P_{it+1} - B_{it+1}) - (P_{it} - B_{it})]$, is related to expected earnings growth.[23]

Penman and Zhu (2014) forecast the forward earnings yield, Y_{it+1}/P_{it}, and the two-year-ahead earnings growth with several anomaly variables, many of which forecast the forward earnings yield and earnings growth in the same direction of forecasting returns. Penman and Zhu (2020) construct

(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.

[23] Intuitively, an increase in the deviation means that price rises more than book equity. Because earnings raises book equity via the clean surplus relation, an expected increase in the deviation means that price increases more than earnings. A lower earnings at $t+1$ relative to price, P_t, must mean higher earnings afterward, as price reflects life-long earnings for the firm. As such, an expected increase in the deviation captures higher expected earnings growth after $t+1$.

a fundamental analysis strategy based on the expected-return proxy from projecting future returns on anomaly variables that are a priori connected to future earnings growth. The expected-return proxy, denoted ER8, is based on 8 variables. We work with ER8 because it is the most comprehensive proxy in their study. The list consists of earnings-to-price, book-to-market, accruals, investment, growth in net operating assets, return on assets, net external financing, and net share issues, all of which are from Compustat annual files (the Internet Appendix, Section B.3).

We largely follow Penman and Zhu (2020) in constructing ER8, except that we adopt the more standard Fama-French (1993) timing for annual sorts. At the end of June of each year t, using the prior 10-year rolling window, we perform annual cross-sectional regressions of stock returns cumulated from July of 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 8 accounting variables for the fiscal year ending in calendar year $t-2$. The other 9 annual regressions in the rolling window are specified accordingly. We winsorize both the left- and right-hand side variables in each regression at the 1–99% level. We combine the average slopes from the 10-year rolling window with the 8 winsorized variables for the fiscal year ending in calendar year $t-1$ to calculate ER8.

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

From Panel A of Table 12, the high-minus-low ER8 decile earns on average 0.74% per month ($t = 4.21$). The q^5 alpha is 0.36%, albeit significant ($t = 2.17$). In the q^5 regression, the investment factor loading is 0.56 ($t = 5.55$), and the expected growth factor loading 0.51 ($t = 4.59$). Intuitively, ER8 contains 2 value metrics, earnings-to-price and book-to-market, which correlate negatively with investment, due to the investment-value linkage (Section 4.2). In addition, Penman and Zhu (2020) select the 8 variables based on their predictive power of earnings growth. Because earnings growth and investment growth tend to be positively correlated, the high-minus-low ER8 decile loads positively on the expected investment growth factor.

From Panel B, the ER8 premium varies inversely with size. The high-minus-low quintile earns on average 0.72%, 0.28%, and 0.5% ($t = 4.42$, 1.96, and 3.5) across micro, small, and big stocks, respectively. The q^5 alpha is 0.59% ($t = 3.74$) in microcaps but insignificant in small stocks, 0.03% ($t = 0.25$), and in big stocks, 0.21% ($t = 1.69$). While the investment factor loadings are consistently large and significant, the expected growth factor loading is significant only in big stocks.

Theoretically, our model differs from the Penman-Zhu model in one crucial aspect. Equation (3) decomposes 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.

4.9 Penman and Zhang's (2020a) Accounting-based Factors

While the investment theory is appealing on economic grounds, it assumes perfect accounting, which does not exist in reality. To make contact with the real data, we need to make auxiliary assumptions on how to measure investment, profitability, and expected growth. The real challenge is to maximize the theory's explanatory power, given a myriad of accounting imperfections. Penman and Zhang (2020a) call into question the accounting treatment underlying the q-factor and q^5 models and propose an alternative accounting-based 3-factor model. In this subsection, we address their critique.

4.9.1 The Penman-Zhang Critique

The Penman-Zhang critique is two-fold. First, investment in the q models, measured as the growth of total assets on the balance sheet, does not include expensed investment, such as research and development, advertising expenditures, employee training. Also, these intangible investments forecast returns with a positive sign, contradicting the investment theory that predicts a negative investment-return relation. Rightfully, Penman and Zhang emphasize that, due to accounting conservatism, investment booked to the balance sheet reflects the low risk associated with future payoffs from the underlying tangible assets. In contrast, investment expensed to the income statement reflects the high risk associated with future payoffs from the underlying intangible assets.

Second, Penman and Zhang (2020a) argue that Roe in the q models is a poor measure of economic profitability. Roe misses the book value of intangible assets in the denominator as well as earnings expensed away from the numerator as intangible investments. Because intangible investments forecast return with a positive sign, conservative accounting causes Roe to predict returns with a negative sign in the data (Penman and Zhang 2020b). Penman and Zhang interpret this evidence as contradicting the investment theory, which predicts a positive profitability-return relation.

4.9.2 Tangible versus Intangible Investments

In contrast to their interpretation, we believe that the accounting treatment underlying the q models is in fact congruent with the Penman-Zhang (2020a, b) view of accounting. On the debate on whether to capitalize intangibles or not, with Lev (2001) and Lev and Gu (2016) on the one side and Penman (2009) and Barker, Lennard, Penman, and Teixeira (2020) on the other, our treatment of accounting data is more aligned with the latter. In particular, our investment factor is built on tangible investments booked to the balance sheet, for which conservative accounting also gives rise to a negative relation with expected returns, in line with the investment theory.

More important, intangible investments are incorporated into the q^5 model via the expected growth factor, which uses Ball et al.'s (2016) operating cash flow as a key instrument (the Internet Appendix, Section B.5). The cash flow includes R&D expenses, which are the most reliably measured intangible investments at the firm level. The cash flow excludes SG&A, a portion of which is likely intangible investments. However, separating the investment from the expense component of SG&A is difficult (Penman and Zhang 2020a, footnote 5). For example, advertising expenses not only produce future revenues (intangible assets) but also yield current revenues (current period expenses). Using cash flow directly to form expected growth sidesteps this measurement problem. As emphasized in Penman (2009), missing intangibles from the balance sheet is not necessarily deficient because their value can be ascertained from the flow variables in the income statement.

The upshot is that the q^5 model treats tangible and intangible investments differently, with the former via the investment factor and the latter via the expected growth factor. This treatment accommodates their different risks and relations with expected returns per conservative accounting.[24] We reject the idea that one should aggregate tangible and intangible investments as well as their book values together. Doing so would destroy the accounting information on their differential risks (Penman and Zhang 2020a). Capitalizing intangibles also involves amortization and impairment under uncertainty, which could contaminate the quality of earnings (Barker et al. 2020).

4.9.3 The Profitability Premium

As noted, because intangible investments forecast return with a positive sign, conservative accounting can cause Roe to predict returns with a negative sign in the data. Penman and Zhang (2020a, b) interpret this evidence as contradicting the investment theory underlying the q models.

While acknowledging the importance of conservative accounting on Roe, we emphasize that its

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

impact is not mutually exclusive from the economic forces underlying the profitability premium postulated in the investment theory. Intuitively, high expected profitability relative to low investment must imply high discount rates, which are required to offset the high expected profitability to yield low net present values of new capital and low investment (Hou, Xue, and Zhang 2015). Hou et al. then use quarterly Roe, which provides the most up-to-date information about future Roe, as their expected profitability proxy. Also, Roe is arguably the most common measure of profitability.

Empirically, the negative Roe-return relation in Penman and Zhang (2020a, b) and the positive Roe-return relation in Hou, Xue, and Zhang (2015) can easily be reconciled. The crux is that the former uses annual sorts but the latter uses monthly sorts. Monthly sorts are natural in light of Hou et al.'s reasoning. Because profitability follows a persistent process, exploiting the up-to-date information in quarterly Roe via monthly sorts yields the most accurate proxy of expected profitability.

Table 13 details the profitability-return relation with different measures of profitability. In Panel A, annual Roe (RoeA) is income before extraordinary items (Compustat annual item IB) divided by 1-year-lagged book equity.[25] To form the RoeA deciles, at the end of June of year t, we sort stocks into deciles on the NYSE breakpoints of RoeA 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 $t+1$. Consistent with Penman and Zhang (2020a, b), the high-minus-low decile earns on average only -0.08% per month ($t = -0.45$).

However, consistent with Hou, Xue, and Zhang (2015), the high-minus-low decile from monthly sorts on quarterly Roe with 1-month hold period (Roe1) earns on average 0.63% per month ($t = 3.03$). The Internet Appendix (Section B.4) details the measurement of quarterly Roe and its monthly sorts, which are in turn from Hou, Xue, and Zhang (2020). The Roe premium drops to

[25] Book equity is stockholders' book equity, plus balance sheet deferred taxes and investment tax credit (item TXDITC) if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat (item SEQ), if it is available. If not, we measure stockholders' equity as the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, we use redemption (item PSTKRV), liquidating (item PSTKL), or par value (item PSTK) for the book value of preferred stock.

0.37% ($t = 1.85$) at the 6-month horizon and further to 0.18% ($t = 0.99$) at the 12-month horizon. From Panel B, book leverage plays only a minor role. Monthly sorts on quarterly return on assets with 1-month holding period (Roa1) still yield a large return spread of 0.53% per month ($t = 2.54$).

Panels C and D explore two alternative profitability measures, operating cash flow-to-lagged assets (Cla) and operating profits-to-lagged equity (Ole). The Internet Appendix details their measurement and portfolio construction (Sections B.7 and B.8). Because both mitigate the impact of conservative accounting on Roe, both yield positive return spreads in annual sorts. For Cla, which adds back, for example, R&D expenses, its profitability premium in annual sorts is 0.55% per month ($t = 3.16$). For Ole, its profitability premium is positive but small, 0.1% ($t = 0.52$).

More important, despite its issue with conservative accounting, Roe performs well in monthly sorts relative to the alternative profitability measures. At the 1-month horizon, for example, the high-minus-low Cla decile earns on average 0.52% per month ($t = 3.24$), and the high-minus-low Ole decile earns 0.57% ($t = 2.84$). Both are lower than 0.63% ($t = 3.03$) for Roe. Indeed, the Roe factor is so strong that it fully subsumes the momentum factor, UMD, in head-to-head factor spanning tests between the q-factor model and the Fama-French (2018) 6-factor model (Hou et al. 2019).

The crux is the unique information advantage for earnings data, which become available in the months immediately after quarterly earnings announcement dates (Compustat quarterly item RDQ). For other quarterly accounting items, we must impose a 4-month lag between the fiscal quarter end and subsequent returns to avoid look-ahead bias.[26] More stale information weakens the predictive power of the alternative profitability measures in monthly sorts. In addition, Roe allows one to start the sample in January 1967 because only quarterly earnings data are required in the numerator. In contrast, because quarterly Cla and Ole require more data items, their samples start later, January 1976 and January 1972, respectively, to ensure at least ten stocks in each decile.

[26]Firms typically announce earnings for a given quarter through press release and file SEC reports several weeks later. Easton and Zmijewski (1993) report a median lag of 46 days for NYSE/Amex firms and 52 days for NASDAQ firms. Chen, DeFond, and Park (2002) show only 37% of quarterly announcements include balance sheet information.

4.9.4 The Penman-Zhang (2020a) 3-factor Model

While maintaining that our accounting treatment underlying the q models is sensible, we are open to further improvement. Penman and Zhang (2020a) propose a different approach of packaging accounting information into a factor model. While our treatment is conceptually congruent with their accounting, we show that their 3-factor model does not improve on the q models. In practice, their factors are fully subsumed by the q models in head-to-head factor spanning tests.

The Penman-Zhang 3-factor model includes the market factor, an investment factor (INV) formed on change in total assets scaled by lagged market equity, and a "grand" portfolio (SUM) that summarizes the salient accounting properties described in Section 4.9.1. At the end of June of each year t, we split stocks into terciles based on the NYSE breakpoints of annual change of total assets (Compustat annual item AT) for the fiscal year ending in calendar year $t-1$ scaled by 1-year-lagged market equity (share price times shares outstanding from CRSP). Monthly value-weighted returns are calculated from July of year t to June of $t+1$, and the terciles are rebalanced at the June-end of $t+1$. INV is the returns of the high-minus-low tercile.

The SUM factor is from sequential $4 \times 3 \times 3$ sorts on earnings-to-price (E/P), annual Roe (RoeA), and expensed investment-to-lagged price (ExpInv/P). E/P is income before extraordinary items (Compustat annual item IB) scaled by the CRSP market equity. RoeA is item IB scaled by 1-year-lagged book equity (footnote 25). ExpInv/P is R&D expenses (item XRD) plus advertising expenses (item XAD) plus 30% of SG&A (item XSGA minus item XAD minus item XRD if positive, otherwise just item XSGA), all scaled by 1-year-lagged market equity from CRSP. If any of the items, XRD, XAD, and XSGA, is missing, we set its missing value to be zero.

At the end of June of each year t, we split stocks into 4 E/P groups based on negative E/P and NYSE breakpoints of positive E/P terciles, in which item IB is from the fiscal year ending in calendar year $t-1$ and the market equity from the December-end of $t-1$. Within each E/P group, we split stocks further into RoeA terciles based on its NYSE breakpoints of RoeA for the fiscal year ending in calendar year $t-1$. Finally, within each E/P-RoeA portfolio, we split stocks further into ExpInv/P terciles based on the NYSE breakpoints of ExpInv/P, in which expensed investment is for the fiscal year ending in calendar year $t-1$, and the market equity for the fiscal year ending in $t-2$. Monthly value-weighted portfolio returns are calculated from July of year t to June of $t+1$, and all the portfolios are rebalanced at the June-end of $t+1$. The SUM factor is the high E/P-low RoeA-high ExpInv/P portfolio minus the low E/P-high RoeA-low ExpInv/P portfolio.

Panel A of Table 14 shows that SUM earns on average 0.52% per month ($t = 2.57$). The q models do a good job in describing the 36 portfolios from the $4 \times 3 \times 3$ sequential sorts. Only 3 out of 36 individual alphas are significant in the q-factor model, and only one in the q^5 model. Neither model can be rejected by the GRS test on the null that the 36 alphas are jointly zero.

Panel B shows head-to-head factor spanning tests. On the one hand, the Penman-Zhang 3-factor model fails to explain the investment, Roe, and expected growth factors, with alphas of 0.27%, 0.65%, and 0.93% per month ($t = 4.45, 7.37$, and 13.58), respectively. The alphas for the Roe and expected growth factors are even larger than their average returns. The GRS test strongly rejects the Penman-Zhang model on the null that the investment and Roe factor alphas, with and without the alpha of the expected growth factor, are jointly zero ($p = 0.00$). On the other hand, both q models reduce the SUM factor to alphas about 0.2% per month, with t-values slightly above one. SUM rides heavily on our investment factor, with a loading of 1.1 and t-values above 11. The Roe factor loading is significantly negative, -0.4, but the expected growth factor loading is tiny. The Penman-Zhang (high-minus-low) investment factor earns only -0.13% ($t = -1.34$), and its q and q^5 alphas are less than 0.07% with t-values below one. The GRS test on the null that the SUM and INV alphas are jointly zero cannot reject the q-factor model ($p = 0.34$) or the q^5 model ($p = 0.49$).

Penman and Zhang (2020a) report that the q models cannot subsume their factors, which, conversely, cannot subsume the q models. In contrast, Table 14 shows that the q models fully subsume their factors. Crucially, Penman and Zhang form their factors on NYSE-Amex-NASDAQ breakpoints and equal-weighted returns, whereas we form ours on NYSE breakpoints and value-weighted returns. Table S8 in the Internet Appendix largely replicates their results. The equal-weighted SUM factor earns on average 1.04% per month ($t = 5.17$), and its q and q^5 alphas are 0.85% ($t = 4.79$) and 0.64% ($t = 3.41$), respectively. The equal-weighted INV factor earns on average -0.53% ($t = -5.42$), and its q and q^5 alphas are -0.57% ($t = -5.16$) and -0.49% ($t = -5.37$), respectively.

However, in our view, this evidence must be interpreted with extreme caution. While sorts with NYSE breakpoints and value-weighting assign modest weights to microcaps (less than 10%), sorts with NYSE-Amex-NASDAQ breakpoints and equal-weighting assign disproportionately large weights (more than 60%) to microcaps (Hou, Xue, and Zhang 2020). Microcaps are tiny, not just small, representing only slightly over 3% of the total market capitalization but accounting for more than 60% of the total number of stocks. Because of the extreme nature of microcaps, equal-weighted factor returns are more apparent than real, with little economic importance. In contrast, value-weighting mitigates the impact of microcaps and reflects the wealth effect experienced by investors. Value-weighting also ensures that we compare apples with apples in factor spanning tests.[27]

5 Summary and Interpretation

This paper attempts to provide an equilibrium foundation for Graham and Dodd (1934). In the investment theory, expected returns vary cross-sectionally, depending on real investment, expected profitability, and expected growth. While realized returns are predictable, abnormal returns are not, thereby retaining efficient markets. We believe that the investment theory provides an economics-based theoretical framework for security analysis, a framework consistent with modern finance but mostly missing from the accounting literature. We also believe that our equilibrium foundation po-

[27]The Internet Appendix reports additional robustness checks, including an alternative measure of expensed investment without SG&A (Table S9) and two alternative measures of earnings-to-price with earnings replaced by operating cash flow (Table S10) and operating profits (Table S11). Without going into the details, we can report that the q models continue to do a good job in subsuming the SUM factor (the INV factor is unchanged from Table 14). The only exception is the q-factor alpha of 0.42% per month ($t = 2.72$) for the SUM factor in Table S9, but its q^5 alpha is 0.19% ($t = 1.13$). The GRS test rejects the q-factor model ($p = 0.01$) but not the q^5 model ($p = 0.43$) (untabulated). The corresponding p-values are 0.57 and 0.7 in Table S10 and 0.45 and 0.67 in Table S11. The GRS test strongly rejects the Penman-Zhang model in all the tables ($p = 0.00$).

tentially makes security analysis more palatable to a broader audience. Empirically, the q^5 model goes a long way in explaining the performance of top-notch active, discretionary value funds and a long list of prominent quantitative strategies grounded in security analysis.

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

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Table 1 : 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 month 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	12/1987	11/1999	144	1.65	1.53	1,884.33
2	AXA Enterprise Funds Trust: AXA Enterprise Small Company Value Fund	5/1997	5/2007	121	1.23	1.08	400.90
3	Oppenheimer Quest Value Fund, Inc	12/1980	11/2007	324	1.23	1.08	506.38
4	Meridian Fund, Inc: Meridian Value Fund	12/1994	8/2013	225	1.22	1.10	882.83
5	Dreyfus Growth & Value Funds, Inc: Dreyfus Emerging Leaders Fund	12/1995	12/2006	133	1.18	1.07	722.22
6	Wasatch Funds Trust: Wasatch Micro Cap Value Fund	12/2004	12/2020	193	1.18	1.00	163.34
7	Wells Fargo Funds Trust: Wells Fargo Special Mid Cap Value Fund	7/2010	12/2020	126	1.11	1.02	4,094.86
8	T. Rowe Price Small-Cap Value Fund, Inc	12/1990	12/2020	361	1.07	1.00	4,658.06
9	Wasatch Funds Trust: Wasatch Small Cap Value Fund	1/1998	12/2020	276	1.07	0.94	397.40
10	Guggenheim Funds Trust: Guggenheim SMid Cap Value Fund	10/1998	12/2020	267	1.06	0.94	796.82
11	RBB Fund, Inc: Boston Partners Small Cap Value II Fund	12/1999	12/2020	253	1.05	0.93	294.85
12	Royce Fund: Royce Value Plus Fund	6/2003	4/2015	143	1.05	0.93	1,620.58
13	Touchstone Strategic Trust: Touchstone Micro Cap Value Fund	12/1998	3/2013	172	1.04	0.91	80.07
14	BNY Mellon Advantage Funds, Inc: BNY Mellon Opportunistic Midcap Value Fund	12/1995	12/2020	301	1.04	0.94	1,005.42
15	CRM Mutual Fund Trust: CRM Mid Cap Value Fund	12/1999	12/2020	253	1.03	0.95	1,719.15
16	Royce Fund:Value Fund	12/1983	5/1997	162	1.02	0.88	147.95
17	Guggenheim Funds Trust: Guggenheim Small Cap Value Fund	10/2008	12/2020	147	1.00	0.88	20.43
18	MassMutual Select Funds: MassMutual Select Focused Value Fund	6/2000	10/2017	209	1.00	0.92	649.20
19	Fenimore Asset Management Trust: FAM Value Fund	12/1990	12/2020	361	0.99	0.89	656.66
20	Advantage Funds, Inc: Dreyfus Small Company Value Fund	1/1994	1/2010	193	0.99	0.89	182.08

Table 2 : Explaining the Performance of Active Value Funds with the q 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 2020. Fund 1, 2, ..., 20 are the top-20 active value funds listed in Table 1, 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 2020. 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, CAPM alpha, q-factor alpha, q^5 alpha, q^5 factor loadings on the market, size, investment, Roe, and expected growth factors, as well as R^2. The t-values beneath the 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}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}	R^2
All, ew	0.78	0.09	−0.06	0.01	0.96	0.23	0.33	0.10	−0.12	0.89
	3.43	0.77	−0.69	0.13	44.45	3.45	5.83	2.07	−1.88	
All, vw	0.75	0.07	−0.14	−0.17	0.99	0.21	0.40	0.09	0.05	0.86
	3.20	0.46	−2.02	−1.63	46.50	2.63	3.84	1.66	0.30	
Top-20, ew	1.00	0.38	0.27	0.33	0.88	0.42	0.30	−0.01	−0.09	0.91
	4.52	3.32	3.46	4.90	31.11	4.95	5.13	−0.26	−1.58	
Top-20, vw	0.90	0.29	0.15	0.24	0.87	0.36	0.28	0.05	−0.13	0.91
	4.22	2.80	2.01	3.68	36.61	5.18	4.67	1.13	−2.13	
1	1.32	0.21	0.23	0.21	0.94	0.09	−0.23	0.18	0.02	0.82
	3.78	1.20	0.90	0.76	15.80	1.01	−1.53	1.58	0.15	
2	1.02	0.63	0.25	0.36	0.81	0.29	0.41	0.08	−0.18	0.83
	2.53	2.88	1.30	1.92	14.27	3.18	4.65	1.10	−1.72	
3	0.84	0.41	−0.00	0.00	0.87	0.02	0.47	0.18	−0.01	0.77
	3.81	3.13	−0.02	0.02	23.48	0.19	5.24	2.71	−0.10	
4	1.10	0.58	0.26	0.17	0.88	0.45	0.23	0.12	0.14	0.83
	3.27	2.96	2.05	1.36	24.29	8.03	3.25	1.64	1.71	
5	1.03	0.43	−0.06	0.01	1.10	0.62	0.20	0.17	−0.10	0.91
	2.08	1.76	−0.33	0.06	18.89	11.86	1.96	1.83	−1.10	
6	1.23	0.33	0.48	0.58	0.85	0.55	−0.51	−0.13	−0.25	0.86
	2.79	1.71	2.85	3.68	14.97	6.60	−5.31	−1.42	−2.39	
7	1.18	−0.17	−0.01	0.20	0.90	0.21	0.02	0.23	−0.52	0.94
	2.95	−0.84	−0.09	1.96	25.24	3.30	0.22	3.25	−3.56	
8	0.98	0.30	0.08	0.16	0.82	0.61	0.41	0.12	−0.12	0.88
	3.81	1.81	0.71	1.64	25.71	7.77	6.06	2.06	−1.80	
9	1.10	0.42	0.29	0.35	0.96	0.62	0.28	0.01	−0.09	0.83
	2.74	1.70	1.60	2.04	13.15	4.21	2.54	0.13	−0.85	
10	1.06	0.42	0.25	0.32	0.92	0.38	0.45	0.03	−0.11	0.82
	3.28	2.16	1.82	2.53	17.39	3.33	4.69	0.33	−1.17	
11	1.10	0.48	0.23	0.33	0.98	0.55	0.55	0.07	−0.18	0.84
	2.83	1.84	1.23	2.05	13.85	3.30	4.39	0.55	−1.17	
12	1.09	0.20	0.25	0.34	0.93	0.75	−0.58	−0.14	−0.26	0.93
	2.20	0.95	1.81	2.67	19.78	12.84	−6.50	−2.32	−2.44	
13	1.02	0.71	0.40	0.45	0.84	0.43	0.48	−0.25	−0.11	0.79
	2.11	2.65	1.50	1.62	9.37	2.67	2.92	−2.00	−0.85	
14	1.07	0.18	0.20	0.27	1.17	0.13	0.23	−0.13	−0.11	0.80
	2.85	0.86	0.92	1.20	14.34	0.86	1.80	−0.88	−1.06	
15	1.01	0.50	0.29	0.32	0.94	0.23	0.32	0.21	−0.05	0.83
	3.28	2.70	2.01	2.26	15.84	2.51	2.86	2.49	−0.61	
16	0.60	0.01	0.24	0.33	0.69	0.55	0.13	−0.15	−0.12	0.93
	1.99	0.10	2.64	3.36	33.36	13.88	2.24	−4.09	−2.42	
17	1.15	−0.11	0.19	0.27	0.88	0.71	0.48	−0.08	−0.16	0.90
	2.30	−0.42	1.00	1.45	15.59	9.00	3.45	−0.85	−1.52	
18	1.01	0.51	0.39	0.31	1.08	0.12	0.40	−0.14	0.19	0.83
	2.63	2.48	2.20	1.83	17.31	1.09	3.46	−1.40	1.24	
19	0.87	0.29	0.01	0.05	0.83	0.21	0.45	0.23	−0.06	0.76
	4.10	1.98	0.10	0.44	18.67	1.91	5.07	2.97	−0.64	
20	0.97	0.45	0.47	0.61	1.10	0.47	0.27	−0.34	−0.20	0.75
	1.70	1.24	1.30	1.55	9.14	2.39	1.50	−1.80	−1.16	

Panel B: Explaining net fund returns										
Funds	Mean	α	α_q	α_{q^5}	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}	R^2
All, ew	0.69	−0.01	−0.16	−0.09	0.96	0.23	0.32	0.10	−0.12	0.89
	3.00	−0.09	−1.76	−1.05	44.64	3.46	5.79	2.07	−1.86	
All, vw	0.66	−0.02	−0.23	−0.26	0.99	0.21	0.40	0.09	0.05	0.86
	2.83	−0.15	−3.27	−2.45	46.66	2.63	3.81	1.65	0.30	
Top-20, ew	0.88	0.26	0.15	0.21	0.88	0.42	0.30	−0.01	−0.09	0.91
	3.97	2.26	1.91	3.11	31.04	4.94	5.09	−0.27	−1.60	
Top-20, vw	0.79	0.17	0.04	0.13	0.87	0.36	0.28	0.05	−0.13	0.91
	3.70	1.71	0.58	2.01	36.52	5.16	4.62	1.11	−2.16	
1	1.20	0.09	0.11	0.09	0.94	0.09	−0.23	0.18	0.01	0.82
	3.45	0.54	0.42	0.34	15.77	1.02	−1.52	1.59	0.12	
2	0.87	0.48	0.09	0.21	0.81	0.29	0.41	0.08	−0.18	0.83
	2.15	2.17	0.48	1.10	14.27	3.18	4.66	1.11	−1.73	
3	0.69	0.26	−0.15	−0.15	0.87	0.02	0.47	0.18	−0.01	0.77
	3.12	1.97	−1.16	−1.08	23.32	0.20	5.22	2.70	−0.12	
4	0.98	0.46	0.14	0.06	0.88	0.45	0.23	0.12	0.14	0.83
	2.92	2.35	1.11	0.44	24.15	8.03	3.25	1.62	1.63	
5	0.92	0.32	−0.16	−0.10	1.10	0.62	0.20	0.17	−0.10	0.91
	1.86	1.32	−0.96	−0.54	18.90	11.87	1.96	1.83	−1.10	
6	1.06	0.16	0.30	0.41	0.85	0.55	−0.52	−0.13	−0.25	0.86
	2.39	0.82	1.81	2.58	14.97	6.59	−5.32	−1.43	−2.39	
7	1.09	−0.26	−0.10	0.11	0.90	0.21	0.02	0.22	−0.52	0.94
	2.73	−1.29	−0.64	1.10	25.26	3.30	0.21	3.24	−3.56	
8	0.90	0.23	0.00	0.08	0.82	0.61	0.41	0.12	−0.12	0.88
	3.52	1.35	0.00	0.85	25.69	7.77	6.05	2.05	−1.81	
9	0.97	0.29	0.16	0.22	0.96	0.61	0.27	0.01	−0.09	0.83
	2.41	1.17	0.88	1.27	13.17	4.20	2.53	0.14	−0.87	
10	0.93	0.29	0.13	0.19	0.92	0.38	0.44	0.03	−0.11	0.82
	2.89	1.51	0.92	1.53	17.41	3.33	4.68	0.34	−1.17	
11	0.97	0.36	0.11	0.21	0.98	0.55	0.55	0.06	−0.18	0.84
	2.52	1.38	0.59	1.30	13.88	3.30	4.38	0.55	−1.17	
12	0.98	0.08	0.14	0.23	0.93	0.75	−0.58	−0.14	−0.26	0.93
	1.97	0.41	0.99	1.78	19.78	12.84	−6.51	−2.31	−2.44	
13	0.89	0.58	0.27	0.32	0.84	0.43	0.48	−0.25	−0.11	0.79
	1.84	2.15	1.00	1.15	9.37	2.67	2.92	−2.00	−0.86	
14	0.97	0.08	0.10	0.17	1.17	0.13	0.22	−0.13	−0.11	0.80
	2.58	0.40	0.47	0.77	14.34	0.86	1.80	−0.88	−1.07	
15	0.93	0.41	0.21	0.24	0.94	0.23	0.32	0.21	−0.06	0.83
	3.01	2.26	1.44	1.68	15.86	2.50	2.86	2.49	−0.62	
16	0.45	−0.13	0.09	0.18	0.69	0.55	0.12	−0.15	−0.12	0.93
	1.51	−0.95	1.04	1.87	33.21	13.83	2.22	−4.05	−2.42	
17	1.03	−0.22	0.07	0.15	0.88	0.71	0.48	−0.08	−0.17	0.90
	2.06	−0.89	0.37	0.82	15.64	9.00	3.46	−0.84	−1.54	
18	0.93	0.43	0.31	0.23	1.08	0.12	0.40	−0.14	0.19	0.83
	2.42	2.09	1.75	1.35	17.29	1.09	3.46	−1.40	1.24	
19	0.77	0.19	−0.09	−0.05	0.83	0.21	0.45	0.23	−0.06	0.76
	3.62	1.28	−0.75	−0.48	18.66	1.91	5.06	2.97	−0.65	
20	0.88	0.35	0.37	0.51	1.10	0.47	0.27	−0.34	−0.19	0.75
	1.54	0.98	1.03	1.30	9.15	2.40	1.51	−1.79	−1.15	

Table 3 : Buffett's Alpha, February 1968–December 2020

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

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

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

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

Sample	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	β_{BAB}	β_{QMJ}	R^2
2/68–12/20	0.58	0.79	−0.12	0.33	−0.01	0.24	0.30	0.20
	2.07	8.99	−0.79	2.50	−0.12	2.51	2.13	
11/76–3/17	0.45	0.93	−0.18	0.40	−0.05	0.27	0.39	0.29
	1.67	10.67	−1.45	3.20	−0.91	2.98	2.79	

Table 4 : The Abarbanell-Bushee (1998) Security Analysis Portfolios, January 1967–December 2020

Section 4.1 details the measurement of the Abarbanell-Bushee composite signal, denoted AB. In Panel A, at the end of June of each year t, we sort stocks into deciles on the NYSE breakpoints of AB for the fiscal year ending in calendar year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. In Panel B, at the end of June of year t, we sort stocks into quintiles based on the NYSE breakpoints of AB for the fiscal year ending in calendar year $t-1$ and, independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the June-end market equity. Taking intersections yields 15 portfolios. The "All" rows report results from one-way AB sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

Panel A: Deciles from one-way sorts on intrinsic-to-market value

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

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

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

Table 5 : The Frankel-Lee (1998) Intrinsic-to-Market Value Portfolios, January 1967–December 2020

Intrinsic-to-market is the intrinsic value, V^h, over the market equity, P. Section 4.2 details the measurement of V^h. In Panel A, at the end of June of each year t, we sort stocks into deciles on the NYSE breakpoints of V^h/P for the fiscal year ending in calendar year $t-1$, in which the market equity is at the end of December of year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. In Panel B, at the end of June of year t, we sort stocks into quintiles based on the NYSE breakpoints of V^h/P for the fiscal year ending in calendar year $t-1$ and, independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the June-end market equity. Taking intersections yields 15 portfolios. The "All" rows report results from one-way V^h/P sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

Panel A: Deciles from one-way sorts on intrinsic-to-market value

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

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

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

Table 6 : The Piotroski (2000) F-score Portfolios, July 1972–December 2020

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

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

	L	2	3	4	5	6	H	H−L				p_{GRS}
$\overline{R}$	0.58	0.44	0.61	0.63	0.63	0.63	0.78	0.20				
$t_{\overline{R}}$	1.69	1.67	3.11	3.33	3.36	3.49	3.84	0.80				
α_q	0.12	−0.07	0.12	0.10	0.02	0.08	0.07	−0.05				0.08
t_q	0.59	−0.65	1.67	1.90	0.30	1.22	0.69	−0.22				
α_{q^5}	0.18	−0.08	0.01	0.08	0.01	0.06	0.08	−0.10				0.55
t_{q^5}	0.72	−0.73	0.19	1.67	0.13	0.79	0.69	−0.36				
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.18	−0.33	0.24	0.71	0.07		−2.72	−2.58	1.68	4.69	0.39	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	0.45	0.61	0.63	0.63	0.67	0.22		1.65	3.11	3.33	3.36	3.70	1.48
Micro	0.67	0.81	0.81	0.94	1.03	0.36		1.91	2.61	2.84	3.45	3.87	2.21
Small	0.59	0.72	0.76	0.87	0.89	0.30		1.86	2.68	3.07	3.63	3.73	2.08
Big	0.45	0.62	0.62	0.61	0.65	0.20		1.68	3.16	3.30	3.27	3.64	1.31
			α_q ($p_{\mathrm{GRS}} = 0.05$)							t_q			
All	−0.03	0.12	0.10	0.02	0.08	0.11		−0.30	1.67	1.90	0.30	1.35	0.85
Micro	0.08	0.16	0.10	0.18	0.19	0.11		0.65	1.54	1.43	2.03	2.03	0.64
Small	−0.07	−0.04	−0.03	0.02	−0.01	0.07		−0.68	−0.65	−0.57	0.32	−0.08	0.51
Big	0.01	0.15	0.11	0.01	0.08	0.07		0.11	2.00	1.93	0.23	1.33	0.48
			α_{q^5} ($p_{\mathrm{GRS}} = 0.19$)							t_{q^5}			
All	−0.04	0.01	0.08	0.01	0.06	0.10		−0.33	0.19	1.67	0.13	0.84	0.65
Micro	−0.06	0.13	0.12	0.19	0.23	0.28		−0.53	1.27	1.56	2.27	2.60	2.19
Small	−0.11	−0.04	−0.02	0.08	0.03	0.14		−1.00	−0.63	−0.34	1.05	0.44	1.04
Big	0.03	0.03	0.09	0.00	0.06	0.04		0.20	0.45	1.73	0.06	0.85	0.22
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	−0.14	−0.18	0.08	0.42	0.03		−3.67	−2.88	0.95	4.58	0.27		0.28
Micro	−0.13	−0.21	0.35	0.62	−0.26		−4.06	−2.44	3.15	6.37	−2.48		0.38
Small	−0.15	−0.15	0.43	0.47	−0.10		−3.86	−2.92	5.04	5.68	−1.04		0.36
Big	−0.14	−0.05	0.07	0.40	0.05		−3.16	−0.75	0.73	3.98	0.46		0.18

Table 7 : The Greenblatt (2010) Portfolios, January 1967–December 2020

A composite score is formed on the percentiles of return on capital and earnings yield (detailed in Section 4.4). 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}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

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

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.40	0.47	0.53	0.58	0.55	0.53	0.57	0.70	0.83	0.96	0.57	
$t_{\overline{R}}$	1.30	2.21	2.86	3.21	2.94	2.79	3.15	3.79	4.68	4.97	2.54	
α_q	0.10	−0.03	−0.01	0.05	−0.03	−0.04	−0.06	0.12	0.16	0.29	0.19	0.04
t_q	0.68	−0.30	−0.17	0.62	−0.47	−0.58	−0.77	1.88	2.31	3.25	1.10	
α_{q^5}	0.18	0.02	−0.02	0.10	0.07	−0.05	−0.10	0.12	0.06	0.05	−0.13	0.42
t_{q^5}	1.30	0.22	−0.24	1.31	0.94	−0.69	−1.12	1.65	0.83	0.57	−0.76	
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.13	−0.20	0.30	0.67	0.48		−3.00	−2.43	2.37	6.26	3.55	0.42

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

	L	2	3	4	H	H−L	L	2	3	4	H	H−L
			$\overline{R}$						$t_{\overline{R}}$			
All	0.44	0.55	0.53	0.63	0.90	0.46	1.84	3.11	2.90	3.57	5.03	3.16
Micro	0.62	0.77	0.86	0.98	0.97	0.35	1.81	2.75	2.97	3.53	3.71	2.05
Small	0.55	0.80	0.79	0.89	0.95	0.40	1.84	3.30	3.26	3.60	3.98	2.49
Big	0.47	0.54	0.52	0.61	0.88	0.41	2.03	3.11	2.86	3.50	5.01	2.70
			α_q ($p_{\mathrm{GRS}}=0.05$)						t_q			
All	0.03	0.01	−0.04	0.01	0.25	0.22	0.32	0.17	−0.81	0.25	4.02	1.76
Micro	0.12	−0.04	0.04	0.09	0.12	0.00	0.85	−0.38	0.47	0.92	1.35	0.01
Small	0.01	−0.05	−0.03	0.00	0.05	0.03	0.15	−0.63	−0.44	0.01	0.58	0.22
Big	0.12	0.03	−0.04	0.01	0.26	0.14	1.08	0.44	−0.71	0.20	3.85	1.03
			α_{q^5} ($p_{\mathrm{GRS}}=0.82$)						t_{q^5}			
All	0.10	0.04	−0.01	−0.03	0.07	−0.03	1.01	0.66	−0.22	−0.48	1.05	−0.24
Micro	0.07	0.06	0.12	0.16	0.14	0.06	0.60	0.64	1.46	1.71	1.58	0.46
Small	0.04	0.04	0.06	0.03	0.08	0.04	0.46	0.51	0.86	0.38	1.03	0.29
Big	0.19	0.06	−0.01	−0.03	0.06	−0.13	1.77	0.83	−0.14	−0.50	0.88	−0.98

	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}	t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
All	−0.11	0.07	0.08	0.42	0.37	−3.12	1.12	0.95	5.21	3.90	0.31
Micro	−0.09	−0.25	0.41	0.67	−0.09	−2.04	−2.06	3.22	6.22	−0.91	0.41
Small	−0.11	−0.09	0.47	0.59	−0.01	−2.21	−0.69	3.92	5.30	−0.08	0.33
Big	−0.10	0.18	0.06	0.42	0.40	−2.61	2.83	0.68	4.85	3.88	0.26

Table 8 : The Asness-Frazzini-Pedersen (2019) Quality Score Portfolios, January 1967–December 2020

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

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

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.44	0.47	0.54	0.52	0.48	0.55	0.58	0.63	0.68	0.73	0.28	
$t_{\overline{R}}$	1.47	2.06	2.50	2.71	2.58	2.97	3.16	3.38	3.74	3.77	1.43	
α_q	−0.06	−0.17	−0.05	−0.08	−0.17	−0.02	−0.02	0.07	0.07	0.32	0.38	0.00
t_q	−0.56	−1.94	−0.47	−1.02	−2.15	−0.29	−0.30	1.31	1.24	4.42	2.82	
α_{q^5}	0.11	−0.03	0.04	−0.03	−0.14	0.04	−0.01	0.11	0.09	0.13	0.02	0.11
t_{q^5}	0.98	−0.41	0.35	−0.33	−1.63	0.59	−0.10	1.94	1.49	1.86	0.15	
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.22	−0.55	−0.62	0.62	0.54		−5.24	−10.67	−7.11	7.81	5.97	0.64

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

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.45	0.52	0.51	0.60	0.71	0.25		1.80	2.67	2.87	3.35	3.81	1.74
Micro	0.41	0.85	0.93	0.97	0.96	0.55		1.13	2.86	3.26	3.50	3.64	3.61
Small	0.59	0.78	0.83	0.82	0.96	0.37		1.93	3.21	3.32	3.34	3.90	2.88
Big	0.48	0.49	0.49	0.59	0.69	0.22		2.01	2.58	2.77	3.30	3.76	1.51
			α_q ($p_{\mathrm{GRS}} = 0.00$)							t_q			
All	−0.13	−0.08	−0.08	0.03	0.23	0.36		−1.66	−1.11	−1.45	0.66	4.21	3.40
Micro	−0.08	0.18	0.19	0.27	0.28	0.36		−0.49	1.47	1.79	2.43	2.41	2.91
Small	0.00	0.04	0.01	0.09	0.23	0.22		0.06	0.64	0.07	1.11	2.87	2.05
Big	−0.08	−0.07	−0.09	0.03	0.23	0.31		−0.85	−0.98	−1.43	0.56	4.07	2.62
			α_{q^5} ($p_{\mathrm{GRS}} = 0.00$)							t_{q^5}			
All	0.01	−0.01	−0.04	0.06	0.11	0.10		0.18	−0.10	−0.69	1.13	2.09	0.97
Micro	0.03	0.26	0.22	0.32	0.29	0.27		0.15	2.17	2.20	2.84	2.52	2.02
Small	0.13	0.11	0.08	0.14	0.21	0.08		1.68	1.57	1.23	2.13	2.72	0.77
Big	0.07	0.00	−0.04	0.05	0.11	0.04		0.69	−0.05	−0.68	1.03	2.00	0.38
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	−0.15	−0.36	−0.59	0.43	0.40		−4.99	−8.83	−8.86	7.06	5.73		0.61
Micro	−0.17	−0.21	0.03	0.63	0.14		−5.75	−4.07	0.33	8.00	1.76		0.49
Small	−0.17	−0.12	−0.10	0.56	0.21		−4.95	−1.33	−1.24	7.03	2.84		0.46
Big	−0.13	−0.22	−0.65	0.40	0.40		−3.76	−5.25	−8.72	5.91	5.06		0.47

Table 9 : The Bartram-Grinblatt (2018) Agnostic Fundamental Analysis Portfolios, January 1977–December 2020

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

Panel A: Deciles from one-way agnostic sorts

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

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

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.69	0.65	0.85	0.91	1.05	0.36		2.82	3.58	4.38	3.93	3.76	1.70
Micro	0.37	0.57	0.93	0.89	1.18	0.81		0.92	1.57	2.85	3.00	3.68	3.71
Small	0.70	0.93	0.88	1.02	1.12	0.42		2.11	3.29	3.30	3.83	3.73	2.09
Big	0.70	0.65	0.85	0.91	1.06	0.36		2.91	3.63	4.49	4.00	3.82	1.59
			α_q ($p_{\text{GRS}} = 0.00$)							t_q			
All	0.09	0.05	0.17	0.14	0.23	0.15		0.80	0.90	2.49	1.04	1.42	0.57
Micro	−0.05	−0.12	0.11	0.00	0.40	0.46		−0.21	−0.53	0.66	0.02	2.13	1.78
Small	0.06	0.13	−0.01	0.11	0.20	0.15		0.52	1.48	−0.14	0.92	1.25	0.61
Big	0.10	0.06	0.19	0.18	0.30	0.20		0.91	1.06	2.73	1.24	1.63	0.73
			α_{q^5} ($p_{\text{GRS}} = 0.00$)							t_{q^5}			
All	0.05	−0.03	0.14	0.25	0.39	0.34		0.52	−0.43	1.85	1.91	2.84	1.60
Micro	0.06	−0.04	0.05	0.01	0.47	0.42		0.19	−0.14	0.28	0.08	2.85	1.62
Small	0.09	0.12	0.00	0.21	0.36	0.27		0.85	1.23	0.05	1.88	2.62	1.33
Big	0.08	−0.02	0.16	0.30	0.44	0.36		0.76	−0.31	2.01	2.03	2.71	1.56
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	0.07	0.34	0.80	−0.18	−0.30		0.96	1.61	4.08	−1.00	−1.85		0.24
Micro	0.01	−0.19	0.59	0.43	0.06		0.09	−1.94	3.23	1.97	0.33		0.19
Small	0.03	−0.33	1.00	0.16	−0.19		0.47	−1.87	5.75	0.80	−1.15		0.23
Big	0.11	0.12	0.73	−0.22	−0.25		1.52	0.61	3.91	−1.20	−1.36		0.14

Table 10 : The Ball-Gerakos-Linnainmaa-Nikolaev (2020) Retained Earnings-to-market Portfolios, January 1967–December 2020

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 β_{Mkt}, β_{Me}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

Panel A: Deciles from one-way sorts on retained earnings-to-market

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.46	0.46	0.64	0.58	0.74	0.70	0.72	0.86	0.81	0.81	0.35	
$t_{\overline{R}}$	1.63	1.97	3.24	3.36	4.31	4.28	3.90	4.81	4.17	3.66	1.66	
α_q	0.01	0.19	0.22	−0.04	0.11	0.00	−0.04	0.05	0.06	0.01	0.00	0.01
t_q	0.11	2.08	2.89	−0.53	1.87	−0.06	−0.47	0.60	0.71	0.10	−0.01	
α_{q^5}	0.18	0.31	0.05	−0.10	0.05	−0.12	−0.11	0.01	0.01	−0.02	−0.20	0.02
t_{q^5}	1.44	3.25	0.73	−1.17	0.83	−1.66	−1.29	0.09	0.14	−0.21	−1.05	
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.04	−0.08	1.19	−0.06	0.30		−0.62	−0.43	6.94	−0.36	2.00	0.27

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	0.43	0.61	0.73	0.77	0.82	0.39		1.77	3.39	4.45	4.36	4.14	2.13
Micro	0.58	0.76	0.92	1.12	1.08	0.50		1.62	2.73	3.55	4.32	4.03	2.45
Small	0.56	0.77	0.93	0.99	0.93	0.38		1.81	3.24	4.09	4.38	3.96	2.01
Big	0.46	0.61	0.72	0.74	0.76	0.29		1.94	3.43	4.44	4.26	3.91	1.60
			α_q ($p_{\mathrm{GRS}}=0.00$)							t_q			
All	0.11	0.09	0.06	−0.01	0.05	−0.06		1.25	1.52	1.23	−0.11	0.60	−0.40
Micro	0.01	0.03	0.14	0.31	0.15	0.14		0.11	0.41	1.34	3.97	1.33	0.69
Small	−0.05	0.03	0.09	0.06	−0.04	0.01		−0.58	0.59	1.37	0.78	−0.44	0.04
Big	0.19	0.10	0.06	−0.02	0.03	−0.15		1.99	1.79	1.18	−0.34	0.34	−1.01
			α_{q^5} ($p_{\mathrm{GRS}}=0.00$)							t_{q^5}			
All	0.25	−0.03	−0.03	−0.08	0.01	−0.25		2.72	−0.58	−0.53	−1.04	0.06	−1.67
Micro	0.03	0.09	0.20	0.31	0.20	0.17		0.25	0.96	2.04	3.63	1.87	0.98
Small	0.03	0.06	0.10	0.10	−0.01	−0.04		0.36	0.99	1.51	1.35	−0.16	−0.31
Big	0.34	−0.02	−0.03	−0.10	−0.02	−0.35		3.39	−0.35	−0.51	−1.25	−0.18	−2.23
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	−0.03	0.18	1.20	−0.05	0.28		−0.74	2.04	10.90	−0.44	2.45		0.38
Micro	−0.13	−0.30	1.05	0.35	−0.05		−2.41	−2.09	6.70	2.40	−0.37		0.40
Small	−0.13	−0.16	1.22	0.14	0.07		−2.40	−1.25	9.14	1.05	0.63		0.43
Big	−0.01	0.20	1.21	−0.09	0.30		−0.12	2.24	10.64	−0.83	2.44		0.35

Table 11 : The Operating Cash Flow-to-market Portfolios, January 1967–December 2020

Operating cash flow, denoted Cop, at the June-end of year t is total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), plus research and development expenditures (item XRD, zero if missing), minus change in accounts receivable (item RECT), minus change in inventory (item INVT), minus change in prepaid expenses (item XPP), plus change in deferred revenue (item DRC plus item DRLT), plus change in trade accounts payable (item AP), and plus change in accrued expenses (item XACC), all from the fiscal year ending in calendar year $t-1$. Missing annual changes are set to zero. In Panel A, at the end of June of year t, we sort stocks into deciles based on the NYSE breakpoints of Cop for the fiscal year ending in calendar year $t-1$ over the December-end market equity (from CRSP). Monthly value-weighted decile returns are from July of year t to June of $t+1$, and the deciles are rebalanced at the end of June of $t+1$. In Panel B, at the end of June of year t, we sort stocks into quintiles based on the NYSE breakpoints of Cop for the fiscal year ending in calendar year $t-1$ over the December-end market equity and, independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the market equity from the June-end of year t. Taking intersections yields 15 portfolios. The "All" rows report results from one-way sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\text{I/A}}$, β_{Roe}, and β_{Eg}, respectively. The t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

Panel A: Deciles from one-way sorts on operating cash flow-to-market

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

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

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

Table 12 : The Penman-Zhu (2020) Expected-return Portfolios, Annually Formed, July 1982–December 2020

The Internet Appendix details the Penman-Zhu annually estimated fundamental measure. In Panel A, at the end of June of year t, we sort stocks into deciles based on the NYSE breakpoints of the Penman-Zhu measure for the fiscal year ending in calendar year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced at the end of June of $t+1$. In Panel B, at the end of June of year t, we sort stocks into quintiles based on the NYSE breakpoints of the Penman-Zhu measure for the fiscal year ending in calendar year $t-1$ and, independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the market equity from the June-end of year t. Taking intersections yields 15 portfolios. The "All" rows report results from one-way sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\text{I/A}}$, 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}
$\overline{R}$	0.31	0.77	0.83	0.73	0.96	0.82	0.92	0.91	1.06	1.05	0.74	
$t_{\overline{R}}$	1.10	2.99	3.87	3.49	4.31	4.42	4.61	4.72	5.09	4.29	4.21	
α_q	−0.51	0.12	0.02	−0.03	0.16	−0.01	0.11	0.08	0.31	0.17	0.68	0.00
t_q	−5.27	1.40	0.22	−0.29	1.36	−0.18	1.46	0.90	3.01	1.34	4.08	
α_{q^5}	−0.33	0.20	0.05	−0.07	0.10	0.01	0.02	−0.04	0.24	0.03	0.36	0.01
t_{q^5}	−3.28	2.39	0.55	−0.68	0.73	0.14	0.23	−0.45	2.46	0.26	2.17	
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.03	−0.25	0.56	−0.15	0.51		−0.70	−3.16	5.55	−1.96	4.59	0.29

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

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.54	0.77	0.89	0.89	1.08	0.54		2.06	3.75	4.51	4.74	5.04	3.93
Micro	0.46	1.01	1.05	1.04	1.18	0.72		1.24	3.09	3.40	3.43	3.98	4.42
Small	0.61	1.05	1.03	1.05	0.90	0.28		1.90	3.73	3.98	4.22	3.32	1.96
Big	0.57	0.76	0.89	0.88	1.07	0.50		2.26	3.76	4.54	4.73	5.06	3.50
			α_q ($p_{\text{GRS}} = 0.00$)							t_q			
All	−0.18	−0.01	0.07	0.08	0.30	0.48		−2.79	−0.09	1.01	1.25	3.42	4.06
Micro	−0.12	0.31	0.32	0.26	0.44	0.57		−1.12	3.11	3.24	2.01	3.45	3.77
Small	−0.16	0.14	0.08	0.13	−0.04	0.11		−2.05	1.78	0.94	1.70	−0.43	0.92
Big	−0.16	−0.01	0.08	0.07	0.31	0.47		−2.21	−0.11	1.01	1.14	3.08	3.47
			α_{q^5} ($p_{\text{GRS}} = 0.00$)							t_{q^5}			
All	−0.05	−0.02	0.05	−0.02	0.19	0.23		−0.74	−0.30	0.59	−0.36	2.24	2.16
Micro	−0.15	0.30	0.26	0.26	0.44	0.59		−1.36	2.93	2.62	1.98	3.18	3.74
Small	−0.07	0.11	0.14	0.16	−0.04	0.03		−0.89	1.15	1.84	2.15	−0.47	0.25
Big	−0.01	−0.02	0.05	−0.03	0.19	0.21		−0.21	−0.31	0.57	−0.46	2.03	1.69
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	−0.05	−0.21	0.61	−0.14	0.39		−1.45	−4.60	6.97	−2.29	5.36		0.43
Micro	−0.11	−0.25	0.46	0.33	−0.04		−2.66	−3.53	3.89	3.69	−0.37		0.37
Small	−0.08	−0.21	0.70	0.15	0.13		−1.83	−3.21	8.32	1.56	1.52		0.42
Big	−0.05	−0.16	0.60	−0.20	0.41		−1.35	−3.04	5.81	−2.84	5.07		0.36

Table 13 : The Profitability-return Relation

Section 4.9 details the measurement of annual Roe and Roa. The Internet Appendix details the measurement of quarterly Roe and Roa as well as operating cash flow-to-lagged assets and operating profits-to-lagged equity, both annual and quarterly. In Panel A, RoeA is annual Roe, and Roe1, Roe6, and Roe12 are quarterly Roe in monthly sorts with 1-, 6-, and 12-month holding period, respectively. The notations in other panels are analogous. In Panel A, for the RoeA deciles, at the end of June of year t, we sort stocks into deciles on the NYSE breakpoints of RoeA 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 $t+1$. The Internet Appendix details the annual sorts on RoaA, ClaA, and OleA as well as the monthly sorts on quarterly Roe, Roa, Cla, and Ole. For each variable, the first row reports average excess returns, and the second row their autocorrelation-and-heteroscedasticity-adjusted t-values.

	Low	2	3	4	5	6	7	8	9	High	H−L
	Panel A: Return on equity (Roe) deciles (January 1967–December 2020)										
RoeA	0.69	0.63	0.58	0.68	0.50	0.60	0.53	0.66	0.61	0.61	−0.08
	2.29	2.81	3.22	4.18	2.80	3.42	2.87	3.61	3.25	2.91	−0.45
Roe1	0.20	0.43	0.46	0.49	0.60	0.52	0.67	0.64	0.63	0.83	0.63
	0.65	1.76	2.14	2.77	3.41	2.73	3.69	3.44	3.44	4.18	3.03
Roe6	0.38	0.45	0.50	0.53	0.62	0.52	0.59	0.63	0.63	0.75	0.37
	1.26	1.89	2.49	3.00	3.61	2.86	3.30	3.45	3.42	3.83	1.85
Roe12	0.50	0.56	0.53	0.54	0.60	0.56	0.60	0.62	0.61	0.68	0.18
	1.70	2.46	2.71	3.14	3.54	3.14	3.38	3.41	3.35	3.48	0.99
	Panel B: Return on assets (Roa) deciles (January 1972–December 2020)										
RoaA	0.57	0.80	0.70	0.58	0.65	0.62	0.74	0.58	0.63	0.64	0.07
	1.87	3.22	3.55	3.21	3.46	3.28	4.01	3.16	3.22	2.95	0.36
Roa1	0.20	0.40	0.52	0.59	0.52	0.63	0.63	0.65	0.66	0.73	0.53
	0.63	1.56	2.22	2.92	2.72	3.15	3.20	3.44	3.31	3.50	2.54
Roa6	0.38	0.45	0.58	0.64	0.55	0.65	0.61	0.67	0.59	0.73	0.35
	1.19	1.73	2.61	3.23	2.93	3.51	3.30	3.55	3.00	3.53	1.75
Roa12	0.47	0.61	0.64	0.64	0.58	0.64	0.63	0.64	0.61	0.69	0.22
	1.55	2.43	3.03	3.18	3.19	3.43	3.44	3.49	3.08	3.37	1.17
	Panel C: Operating cash flow-to-lagged assets (Cla) deciles (January 1976–December 2020)										
ClaA	0.25	0.65	0.53	0.72	0.65	0.85	0.77	0.75	0.78	0.80	0.55
	0.85	2.44	2.26	3.16	3.42	4.14	3.92	3.97	4.07	3.69	3.16
Cla1	0.43	0.33	0.45	0.42	0.69	0.73	0.73	0.84	0.84	0.95	0.52
	1.50	1.27	1.89	1.76	3.27	3.66	3.64	4.25	4.47	4.19	3.24
Cla6	0.45	0.49	0.53	0.60	0.64	0.74	0.76	0.78	0.78	0.91	0.46
	1.72	2.04	2.31	2.66	3.09	3.81	3.94	3.99	4.11	4.06	3.51
Cla12	0.47	0.47	0.54	0.63	0.61	0.73	0.74	0.80	0.79	0.91	0.44
	1.84	1.91	2.41	2.84	2.98	3.81	3.79	4.17	4.19	4.19	3.53
	Panel D: Operating profits-to-lagged equity (Ole) deciles (January 1972–December 2020)										
OleA	0.50	0.54	0.56	0.61	0.66	0.65	0.70	0.60	0.76	0.60	0.10
	1.67	2.47	3.03	3.24	3.63	3.37	3.68	3.28	3.93	2.79	0.52
Ole1	0.22	0.42	0.55	0.52	0.47	0.45	0.77	0.69	0.79	0.79	0.57
	0.69	1.81	2.55	2.62	2.46	2.31	3.98	3.51	4.04	3.73	2.84
Ole6	0.39	0.50	0.48	0.54	0.54	0.56	0.74	0.66	0.73	0.74	0.35
	1.29	2.20	2.40	2.80	2.84	2.99	3.85	3.53	3.75	3.46	1.83
Ole12	0.44	0.55	0.56	0.52	0.55	0.59	0.66	0.60	0.74	0.69	0.26
	1.47	2.43	2.87	2.69	2.91	3.21	3.39	3.19	3.91	3.25	1.41

Table 14 : The Penman-Zhang (2020a) Accounting-based Factors

Section 4.9 details the measurement of annual earnings-to-price (E/P), annual return on equity (RoeA), and expensed investment-to-lagged price (ExpInv/P). Panel A reports the $4 \times 3 \times 3$ portfolios from sequential sorts on E/P, annual Roe, and ExpInv/P. At the end of June of each year t, we split stocks into 4 E/P groups based on negative E/P and NYSE breakpoints of positive E/P. Within each E/P portfolio, we split stocks into 3 RoeA portfolios on its NYSE breakpoints. Finally, within each E/P-RoeA portfolio, we split stocks into 3 ExpInv/P portfolios based on its NYSE breakpoints. Monthly value-weighted returns are calculated from July of year t to June of $t+1$, and the portfolios are rebalanced in June-end of $t+1$. The SUM portfolio is the high E/P-low RoeA-high ExpInv/P portfolio minus the low E/P-high RoeA-low ExpInv/P portfolio. Columns denoted "Col. 3−7" show the results for the Low RoeA-High ExpInv/P portfolio minus the high RoeA-low ExpInv/P portfolio. In Panel B, the Penman-Zhang investment factor (INV) is the value-weighted high-minus-low tercile returns from annual one-way sorts based on the NYSE breakpoints of INV/P (change in total assets scaled by lagged market equity). All t-values are adjusted for autocorrelations and heteroscedasticity.

Panel A: The Penman-Zhang $4 \times 3 \times 3$ benchmark portfolios on E/P, annual Roe, and ExpInv/P

RoeA	Low	Low	Low	M	M	M	High	High	High	Col.	Low	Low	Low	M	M	M	High	High	High	Col.
ExpInv/P	Low	M	High	Low	M	High	Low	M	High	3−7	Low	M	High	Low	M	High	Low	M	High	3−7
	Average excess returns, $\overline{R}$										$t_{\overline{R}}$									
E/P<0	0.09	0.59	0.99	0.46	1.00	0.76	1.03	0.72	0.84	−0.04	0.21	1.46	2.55	1.33	2.96	1.95	3.21	2.27	2.57	−0.14
Low E/P	0.35	0.47	0.92	0.19	0.55	0.69	0.41	0.67	0.69	0.51	1.57	2.10	3.54	0.86	2.69	3.14	1.77	3.35	3.13	2.87
M	0.53	0.51	0.89	0.43	0.72	0.84	0.59	0.65	0.90	0.31	3.39	2.16	4.04	2.31	3.89	3.97	2.77	3.36	4.42	1.68
High E/P	0.71	0.85	0.93	0.63	0.90	1.00	0.63	0.95	0.79	0.30	3.80	3.65	3.70	3.47	4.29	4.51	3.07	4.25	3.29	1.55
SUM										0.52										2.57
	The q-factor alpha, α_q ($p_{\text{GRS}} = 0.12$)										t_q									
E/P<0	−0.31	0.24	0.48	−0.20	0.31	0.16	0.22	0.18	0.21	0.26	−1.09	0.97	2.01	−0.76	1.47	0.63	0.96	0.92	0.97	0.79
Low E/P	−0.35	−0.16	0.26	−0.36	−0.06	0.07	−0.06	0.10	0.10	0.32	−2.61	−1.28	1.89	−2.88	−0.62	0.55	−0.69	1.02	1.04	1.98
M	−0.09	−0.28	0.12	−0.25	0.01	0.01	−0.05	−0.00	0.08	0.17	−0.77	−1.91	0.87	−2.28	0.14	0.13	−0.43	−0.02	0.77	0.90
High E/P	0.01	0.12	0.13	0.05	0.23	0.24	−0.07	0.15	0.07	0.20	0.08	0.89	0.84	0.38	1.71	1.91	−0.46	1.15	0.48	0.92
SUM										0.20										0.19
	The q^5 alpha, α_{q^5} ($p_{\text{GRS}} = 0.41$)										t_{q^5}									
E/P<0	−0.10	0.09	0.32	0.20	0.12	−0.14	0.60	0.19	0.00	−0.29	−0.33	0.36	1.27	0.68	0.55	−0.51	2.33	0.95	0.00	−0.83
Low E/P	−0.21	−0.16	0.17	−0.22	−0.09	0.07	−0.07	0.05	0.09	0.25	−1.52	−1.22	1.19	−1.74	−0.81	0.60	−0.76	0.53	0.87	1.45
M	−0.06	−0.21	0.12	−0.18	0.01	0.04	−0.13	−0.07	0.01	0.26	−0.48	−1.52	0.89	−1.56	0.08	0.38	−1.10	−0.49	0.10	1.35
High E/P	0.07	0.20	0.12	0.14	0.15	0.16	−0.06	0.03	0.09	0.18	0.43	1.40	0.76	1.03	1.11	1.22	−0.44	0.21	0.61	0.83
SUM										0.19										1.04

Panel B: Factor spanning tests between the Penman-Zhang 3-factor model and the q models

	$\overline{R}$	α	β_{Mkt}	β_{SUM}	β_{INV}	R^2
R_{Me}	0.27	0.08	0.16	0.26	0.24	0.26
[t]	2.22	0.76	6.53	9.24	4.50	
$R_{\text{I/A}}$	0.33	0.27	−0.10	0.15	−0.35	0.47
[t]	4.10	4.45	−5.36	10.15	−7.61	
R_{Roe}	0.51	0.65	−0.11	−0.18	−0.11	0.17
[t]	4.96	7.37	−3.40	−6.16	−1.33	
R_{Eg}	0.80	0.93	−0.19	−0.05	−0.11	0.26
[t]	9.69	13.58	−8.88	−3.03	−1.98	

	$\overline{R}$	α	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}	R^2
SUM	0.52	0.20	0.01	0.56	1.10	−0.40		0.39
[t]	2.57	1.09	0.28	7.66	11.17	−4.61		
		0.19	0.01	0.56	1.10	−0.40	0.01	0.39
[t]		1.04	0.30	7.66	11.18	−3.86	0.11	
INV	−0.13	0.07	0.02	0.11	−0.61	−0.07		0.31
[t]	−1.34	0.79	0.47	2.36	−7.76	−1.26		
		0.05	0.02	0.11	−0.62	−0.09	0.04	0.31
[t]		0.49	0.64	2.23	−8.74	−1.47	0.47	

The Internet Appendix
(for Online Publication Only)

A Derivations

We follow Liu, Whited, and Zhang (2009) in proving equation (1). Let q_t be the Lagrangian multiplier for the capital accumulation equation $A_{t+1} = (1-\delta)A_t + I_t$. Form the Lagrangian function:

$$\mathcal{L} = \ldots + X_t A_t - \frac{a}{2}\left(\frac{I_t}{A_t}\right)^2 A_t - I_t - q_t(A_{t+1} - (1-\delta)A_t - I_t)$$
$$+E_t\left[M_{t+1}\left[X_{t+1}A_{t+1} - \frac{a}{2}\left(\frac{I_{t+1}}{A_{t+1}}\right)^2 A_{t+1} - I_{t+1} - q_{t+1}(A_{t+2} - (1-\delta)A_{t+1} - I_{t+1})\right]\right] + \ldots \qquad \text{(S1)}$$

The first-order conditions with respect to I_t and A_{t+1} are, respectively,

$$q_t = 1 + a\frac{I_t}{A_t}; \qquad \text{(S2)}$$
$$q_t = E_t\left[M_{t+1}\left[X_{t+1} + \frac{a}{2}\left(\frac{I_{t+1}}{A_{t+1}}\right)^2 + (1-\delta)q_{t+1}\right]\right]. \qquad \text{(S3)}$$

We start with $P_t + D_t = V_t$ and expand V_t:

$$\begin{aligned} P_t + X_tA_t - \frac{a}{2}\left(\frac{I_t}{A_t}\right)^2 A_t - I_t &= X_tA_t - a\frac{I_t}{A_t}I_t + \frac{a}{2}\left(\frac{I_t}{A_t}\right)^2 A_t - I_t \\ &- q_t(A_{t+1} - (1-\delta)A_t - I_t) + E_t\Bigg[M_{t+1}\Bigg(X_{t+1}A_{t+1} - a\frac{I_{t+1}}{A_{t+1}}I_{t+1} \\ &+\frac{a}{2}\left(\frac{I_{t+1}}{A_{t+1}}\right)^2 A_{t+1} - I_{t+1} - q_{t+1}(A_{t+2} - (1-\delta)A_{t+1} - I_{t+1}) + \ldots\Bigg)\Bigg]. \end{aligned} \qquad \text{(S4)}$$

Substituting equations (S2) and (S3), and using the linear homogeneity of adjustment costs:

$$P_t = \left(1 + a\frac{I_t}{A_t}\right) I_t + q_t(1-\delta)A_t = q_tA_{t+1}. \qquad \text{(S5)}$$

Finally, the cost of capital (the stock return):

$$\begin{aligned} r_{t+1} &= \frac{P_{t+1} + X_{t+1}A_{t+1} - (a/2)\left(I_{t+1}/A_{t+1}\right)^2 A_{t+1} - I_{t+1}}{P_t} \\ &= \frac{q_{t+1}(I_{t+1} + (1-\delta)A_{t+1}) + X_{t+1}A_{t+1} - (a/2)\left(I_{t+1}/A_{t+1}\right)^2 A_{t+1} - I_{t+1}}{q_tA_{t+1}} \\ &= \frac{(1-\delta)q_{t+1} + X_{t+1} + (a/2)\left(I_{t+1}/A_{t+1}\right)^2}{q_t}, \end{aligned} \qquad \text{(S6)}$$

in which the second equality follows from equation (S2), and the third equality follows from the linear homogeneity of the adjustment costs function.

B Measurement

B.1 Piotroski's (2000) Fundamental Score

Piotroski (2000) chooses nine fundamental signals to measure three areas of a firm's financial condition, profitability, liquidity, and operating efficiency. Each signal is classified as either good or bad (one or zero), depending on its implications for future stock prices and profitability. The aggregate signal, denoted F, is the sum of the nine binary signals.

Four profitability variables: (i) Roa is income before extraordinary items (Compustat annual item IB) scaled by 1-year-lagged assets (item AT). If the firm's Roa is positive, the indicator variable F_{Roa} equals one and zero otherwise. (ii) Cf/A is cash flow from operation scaled by 1-year-lagged assets. Cash flow from operation is net cash flow from operating activities (item OANCF) if available, or funds from operation (item FOPT) minus the annual change in working capital (item WCAP). If the firm's Cf/A is positive, the indicator variable $F_{\mathrm{Cf/A}}$ equals one and zero otherwise. (iii) dRoa is the current year's Roa less the prior year's Roa. If dRoa is positive, the indicator variable F_{dROA} is one and zero otherwise. (iv) The indicator F_{Acc} equals one if Cf/A > Roa and zero otherwise.

Three variables measure changes in capital structure and a firm's ability to meet debt obligations. An increase in leverage, a deterioration of liquidity, or the use of external financing is assumed to be a bad signal. (i) dLever is the change in the ratio of total long-term debt (Compustat annual item DLTT) to the average of current and 1-year-lagged total assets. F_{dLever} is one if the firm's leverage ratio falls, dLever < 0, and zero otherwise. (ii) dLiquid measures the change in a firm's current ratio from the prior year, in which the current ratio is the ratio of current assets (item ACT) to current liabilities (item LCT). An improvement in liquidity (ΔdLiquid > 0) is a good signal about the firm's ability to service current debt obligations. The indicator F_{dLiquid} equals one if the firm's liquidity improves and zero otherwise. (iii) The indicator, Eq, equals one if the firm does not issue common equity in the current year and zero otherwise. The issuance of common equity is sales of common and preferred stocks (item SSTK) minus any increase in preferred stocks (item PSTK). Issuing equity is a bad signal (inability to generate sufficient internal funds to service future obligations).

Two signals measure changes in a firm's operation efficiency. (i) dMargin is the firm's current gross margin ratio, measured as gross margin (Compustat annual item SALE minus item COGS) scaled by sales (item SALE), less the prior year's gross margin ratio. An improvement in margins signifies a potential improvement in factor costs, a reduction in inventory costs, or a rise in the price of the firm's product. The indictor F_{dMargin} equals one if dMargin > 0 and zero otherwise. (ii) dTurn is the firm's current year asset turnover ratio, measured as total sales scaled by 1-year-lagged total assets (item AT), minus the prior year's asset turnover ratio. An improvement in asset turnover ratio signifies greater productivity from the asset base. The indicator, F_{dTurn}, equals one if dTurn > 0 and zero otherwise. The composite score, F, is the sum of the individual binary signals:

$$F \equiv F_{\mathrm{Roa}} + F_{\mathrm{dRoa}} + F_{\mathrm{Cf/A}} + F_{\mathrm{Acc}} + F_{\mathrm{dMargin}} + F_{\mathrm{dTurn}} + F_{\mathrm{dLever}} + F_{\mathrm{dLiquid}} + \mathrm{Eq}. \tag{S7}$$

B.2 Asness, Frazzini, and Pedersen's (2019) Quality Score

We closely follow the variable definitions in Aseness, Frazzini, and Pedersen (2019), who consider two versions of quality score. The benchmark score is the average of the profitability, growth, and safety scores, and the alternative score is the average of these three measures as well as a payout score. The profitability score is based on six variables:

1. Gross profitability, measured as total revenue (Compustat annual item REVT) minus costs of goods sold (item COGS) scaled by (current, not lagged) total assets (item AT).

2. Return on equity, measured as income before extraordinary items (item IB) scaled by (current, not lagged) book equity. Following Davis, Fama, and French (2000), we measure book equity as stockholders' book equity, plus balance sheet deferred taxes and investment tax credit (item TXDITC) if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat (item SEQ), if available. If not, we measure stockholders' equity as the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, we use redemption (item PSTKRV), liquidating (item PSTKL), or par value (item PSTK) for the book value of preferred stock.

3. Return on assets, measured as income before extraordinary items (item IB) scaled by (current, not lagged) total assets (item AT).

4. Cash flow over assets, measured as income before extraordinary items plus depreciation minus changes in working capital and capital expenditure, all scaled by current total assets, (IB + DP $-$ $\triangle$ WC $-$ CAPX)/AT. Working capital, WC, is current assets minus current liabilities minus cash and short-term instruments plus short-term debt and income taxes payable (item ACT $-$ LCT $-$ CHE + DLC + TXP). Missing changes in income taxes payable are set to zero.

5. Gross margin, measured as total revenue minus costs of goods sold scaled by current total sales, (RETV $-$ COGS)/SALE.

6. Negative accrual, measured as the depreciation minus changes in working capital scaled by current total assets, $-$($\triangle$WC $-$ DP)/AT.

Each month we first convert each of the six variables into cross-sectional rankings and then take the z-score of the rankings. Taking the z-score means that we divide the cross-sectionally demeaned value of the rankings by the cross-sectional standard deviation of the rankings. The profitability z-score is the average z-score across the six variables.

The growth z-score is the average of the z-scores of the rankings of the 5-year per share growth of residual gross profitability, residual return on equity, residual return on assets, residual cash flow over assets, and residual gross margin. The 5-year per share growth in residual gross profitability is defined as $[(\text{gp}_t - r^f_{t-1,t}\text{at}_{t-1}) - (\text{gp}_{t-5} - r^f_{t-6,t-5}\text{at}_{t-6})]/\text{at}_{t-5}$, in which GP = REVT $-$ COGS, and lowercase names indicate per share quantity (e.g., gp = GP/S, at = AT/S, with S being the split-adjusted number of shares outstanding, item CSHO times AJEX) and $\text{gp}_t - r^f_{t-1,t}\text{at}_{t-1}$ is the residual profit in fiscal year t. $r^f_{t-1,t}$ is the 12-month risk-free rate from the end of fiscal year $t-1$ to the end of fiscal year t from accumulating 1-month T-bill rates for the corresponding 12 months. Analogously, 5-year per share growth in residual return on equity is $[(\text{ib}_t - r^f_{t-1,t}\text{be}_{t-1}) - (\text{ib}_{t-5} - r^f_{t-6,t-5}\text{be}_{t-6})]/\text{be}_{t-5}$, 5-year growth in residual return on assets is $[(\text{ib}_t - r^f_{t-1,t}\text{at}_{t-1}) - (\text{ib}_{t-5} - r^f_{t-6,t-5}\text{at}_{t-6})]/\text{at}_{t-5}$, 5-year growth in residual cash flow over assets is $[(\text{cf}_t - r^f_{t-1,t}\text{at}_{t-1}) - (\text{cf}_{t-5} - r^f_{t-6,t-5}\text{at}_{t-6})]/\text{at}_{t-5}$, in which CF = IB + DP $-$ $\triangle$WC $-$ CAPX, and 5-year growth in residual gross margin is $(\text{gp}_t - \text{gp}_{t-5})/\text{sale}_{t-5}$.

The safety z-score is the average of the z-scores of the rankings of low beta, low leverage, low bankruptcy risk (O-score and Z-score), and low earnings volatility. Beta is the minus Frazzini-Pedersen beta. We estimate the beta for stock i as $\hat{\rho}\hat{\sigma}_i/\hat{\sigma}_m$, in which $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated return volatilities for the stock and the market, and $\hat{\rho}$ is their return correlation. To estimate return volatilities, we compute the standard deviations of daily log returns over a 1-year rolling window (with at least 120 daily returns). To estimate return correlations, we use overlapping 3-day log returns, $r_{it}^{3d} = \sum_{k=0}^{2} \log(1 + r_{t+k}^{i})$, over a 5-year rolling window (with at least 750 daily returns).

Leverage is minus total debt (the sum of long-term debt, short-term debt, minority interest, and preferred stock) over current total assets, $-$(DLTT+DLC+MIBT+PSTK)/AT. We take the minus Ohlson's O-score. We follow Ohlson (1980, Model 1 in Table 4) to construct O-score:

$$\begin{aligned} \text{O} \equiv\ & -1.32 - 0.407\log(\text{TA}) + 6.03\text{TLTA} - 1.43\text{WCTA} + 0.076\text{CLCA} \\ & -1.72\text{OENEG} - 2.37\text{NITA} - 1.83\text{FUTL} + 0.285\text{IN2} - 0.521\text{CHIN}, \end{aligned} \tag{S8}$$

in which TA is total assets (Compustat annual item AT). TLTA is the leverage ratio, measured as total debt (item DLC plus DLTT) divided by total assets. WCTA is working capital (item ACT minus LCT) divided by total assets. CLCA is current liability (item LCT) divided by current assets (item ACT). OENEG is one if total liabilities (item LT) exceeds total assets and zero otherwise. NITA is net income (item NI) divided by total assets. FUTL is the fund provided by operations (item PI plus DP) divided by total liabilities. IN2 is equal to one if net income is negative for the last two years and zero otherwise. CHIN is $(\text{NI}_s - \text{NI}_{s-1})/(|\text{NI}_s| + |\text{NI}_{s-1}|)$, in which NI_s and NI_{s-1} are the net income for the current and prior years.

Z-score is Altman's Z-Score, which is the weighted sum of working capital, retained earnings, earnings before interest and taxes, market equity and sales, scaled by current total assets: Z = (1.2WC + 1.4RE + 3.3EBIT + 0.6ME + SALE)/AT. Earnings volatility is the minus standard deviation of quarterly return on equity over the prior 60 quarters (12 minimum), in which quarterly return on equity is income before extraordinary items (Compustat quarterly item IBQ) divided by current quarter book equity. Book equity is shareholders' equity, plus balance sheet deferred taxes and investment tax credit (item TXDITCQ) if available, minus the book value of preferred stock (item PSTKQ). Depending on availability, we use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the book value of preferred stock, or total assets (item ATQ) minus total liabilities (item LTQ) in that order as shareholders' equity.

The payout z-score is the average of the z-scores of the rankings of equity net issuance, debt net issuance, and total net payout over profits. Equity net issuance is the minus of the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year ending in calendar year $t-1$ to the split-adjusted shares outstanding at the fiscal year ending in $t-2$. The split-adjusted shares outstanding is shares outstanding (Compustat annual item CSHO) times the adjustment factor (item AJEX). Debt net issuance is the minus of the natural log of the ratio of total debt (the sum of items DLTT, DLC, MIBT, and PSTK) at the fiscal year ending in calendar year $t-1$ to the total debt at the fiscal year ending in $t-2$. The total net payout-to-profits ratio is the sum of total net payout (income before extraordinary items (item IB) minus the change in book equity) over the past five years divided by total profits (REVT $-$ COGS) over the past five years.

The benchmark quality score is the average across the profitability, growth, and safety z-scores. The alternative quality score is the average across the profitability, growth, safety, and payout z-scores. To determine when each component signal is known publicly, we use annual Fama-French (1993) timing (i.e., variables in fiscal year ending in year $t-1$ are known publicly at the June-end of year t), except for beta and earnings volatility. We consider beta as known publicly at the end of estimation month and earnings volatility as known publicly four months after the fiscal quarter when it is estimated. We use monthly sorts on the quality scores and their components to construct portfolios with NYSE breakpoints, value-weighted returns, and 1-month holding period.

B.3 Penman and Zhu's (2020) Expected-return Measure

We construct the Penman-Zhu ER8 measure using the following eight anomaly variables:

1. Earnings-to-price, Ep: Income before extraordinary items (Compustat annual item IB) for the fiscal year ending in calendar year $t-1$ divided by the market equity (from CRSP) at the same fiscal year end. For firms with more than one share class, we merge the market equity for all share classes before computing Ep.

2. Book-to-market equity, Bm: The book equity for the fiscal year ending in calendar year $t-1$ divided by the market equity (from CRSP) at the same fiscal year end. For firms with more than one share class, we merge the market equity for all share classes before computing Bm. Following Davis, Fama, and French (2000), we measure book equity as stockholders' book equity, plus balance sheet deferred taxes and investment tax credit (Compustat annual item TXDITC) if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat (item SEQ), if it is available. If not, we measure stockholders' equity as the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, we use redemption (item PSTKRV), liquidating (item PSTKL), or par value (item PSTK) for the book value of preferred stock. We keep only firms with positive book equity.

3. Return on assets, Roa: Income before extraordinary items (Compustat annual item IB) divided by lagged assets (item AT).

4. Accruals, Acc: Accruals for the current fiscal year divided by average total assets (Compustat annual item AT) over the current and last fiscal years. We measure accruals as the sum of change in accounts receivable (item RECT), change in inventory (item INVT), and change in other current assets (item ACO), minus the sum of change in accounts payable (item AP) and change in other current liabilities (item LCO), minus depreciation and amortization expense (item DP). Missing ACO, AP, LCO, and DP are set to zero.

5. Investment, dPia: The annual change in gross property, plant, and equipment (Compustat annual item PPEGT) plus the annual change in inventory (item INVT) scaled by 1-year-lagged total assets (item AT).

6. Growth in net operating assets, dNoa: We measure net operating assets as operating assets minus operating liabilities. Operating assets are total assets (Compustat annual item AT) minus cash and short-term investment (item CHE). Operating liabilities are total assets minus debt included in current liabilities (item DLC, zero if missing), minus long-term debt (item DLTT, zero if missing), minus minority interests (item MIB, zero if missing), minus preferred stocks (item PSTK, zero if missing), and minus common equity (item CEQ). dNoa, is the annual change in net operating assets scaled by 1-year-lagged total assets.

7. Net external financing, Nxf: Net external financing for the fiscal year ending in calendar year $t-1$ scaled by the average of total assets for fiscal years ending in $t-2$ and $t-1$. Net external financing is the sum of net equity financing, Nef, and net debt financing, Ndf. Nef is the

proceeds from the sale of common and preferred stocks (Compustat annual item SSTK) less cash payments for the repurchases of common and preferred stocks (item PRSTKC) less cash payments for dividends (item DV). Ndf is the cash proceeds from the issuance of long-term debt (item DLTIS) less cash payments for long-term debt reductions (item DLTR) plus the net changes in current debt (item DLCCH, zero if missing). The data on financing activities start in 1971.

8. Net share issues, Nsi: we measure Nsi as the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year ending in calendar year $t-1$ to the split-adjusted shares outstanding at the fiscal year ending in $t-2$. The split-adjusted shares outstanding is shares outstanding (Compustat annual item CSHO) times the adjustment factor (item AJEX).

B.4 Return on Equity (Roe)

Annual Roe (RoeA) is income before extraordinary items (Compustat annual item IB) divided by 1-year-lagged book equity. Book equity is stockholders' book equity, plus balance sheet deferred taxes and investment tax credit (item TXDITC) if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat (item SEQ), if it is available. If not, we measure stockholders' equity as the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, we use redemption (item PSTKRV), liquidating (item PSTKL), or par value (item PSTK) for the book value of preferred stock. To form the RoeA deciles, at the end of June of year t, we sort stocks into deciles on the NYSE breakpoints of RoeA 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 $t+1$.

We measure quarterly Roe per Hou, Xue, and Zhang (2020). Roe is income before extraordinary items (Compustat quarterly item IBQ) divided by 1-quarter-lagged book equity. Book equity is shareholders' equity, plus balance sheet deferred taxes and investment tax credit (item TXDITCQ) if available, minus the book value of preferred stock (item PSTKQ). Depending on availability, we use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the book value of preferred stock, or total assets (item ATQ) minus total liabilities (item LTQ) in that order as shareholders' equity. Before 1972, the sample coverage is limited for quarterly book equity in Compustat quarterly files. We expand the coverage by using book equity from Compustat annual files as well as by imputing quarterly book equity with clean surplus accounting. Whenever available we first use quarterly book equity from Compustat quarterly files. We then supplement the coverage for fiscal quarter four with annual book equity from Compustat annual files. Following Davis, Fama, and French (2000), we measure annual book equity as stockholders' book equity, plus balance sheet deferred taxes and investment tax credit (Compustat annual item TXDITC) if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat (item SEQ), if available. If not, stockholders' equity is the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, we use redemption (item PSTKRV), liquidating (item PSTKL), or par value (item PSTK) for the book value of preferred stock.

If both approaches are unavailable, we apply the clean surplus relation to impute the book equity. First, if available, we backward impute the beginning-of-quarter book equity as the end-of-quarter book equity minus quarterly earnings plus quarterly dividends. Quarterly earnings are income before extraordinary items (Compustat quarterly item IBQ). Quarterly dividends are zero if dividends per share (item DVPSXQ) are zero. Otherwise, total dividends are dividends per share times beginning-of-quarter shares outstanding adjusted for stock splits during the quarter. Shares outstanding are from Compustat (quarterly item CSHOQ supplemented with annual item CSHO for fiscal quarter 4) or CRSP (item SHROUT), and the share adjustment factor is from Compustat (quarterly item AJEXQ supplemented with annual item AJEX for fiscal quarter 4) or CRSP (item CFACSHR). If data are unavailable for the backward imputation, we impute the book equity for quarter t forward based on book equity from prior quarters. Let BEQ_{t-j}, $1 \leq j \leq 4$ denote the latest available quarterly book equity as of quarter t, and $\text{IBQ}_{t-j+1,t}$ and $\text{DVQ}_{t-j+1,t}$ be the sum of quarterly earnings and quarterly dividends from quarter $t-j+1$ to t, respectively. BEQ_t can then be imputed as $\text{BEQ}_{t-j} + \text{IBQ}_{t-j+1,t} - \text{DVQ}_{t-j+1,t}$. We do not use prior book equity from more than 4 quarters ago (i.e., $1 \leq j \leq 4$) to reduce imputation errors.

At the beginning of each month t, we sort all stocks into deciles based on their most recent past Roe. Before 1972, we use the most recent Roe computed with quarterly earnings from fiscal quarters ending at least 4 months prior to the portfolio formation. Starting from 1972, we use Roe computed with quarterly earnings from the most recent quarterly earnings announcements (Compustat quarterly item RDQ). For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent Roe to be within 6 months prior to the portfolio formation. This restriction is imposed to exclude stale earnings information. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end. Monthly decile returns are calculated for the current month t (Roe1), from month t to $t+5$ (Roe6), and from month t to $t+11$ (Roe12). The deciles are rebalanced monthly. Holding periods longer than one month like in Roe6 mean that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six months. We average the subdecile returns as the monthly return of the Roe6 decile.

B.5 Expected Growth (Eg)

We measure expected growth, Eg, per Hou, Mo, Xue, and Zhang (2019). At the beginning of each month t, we measure current investment-to-assets as total assets (Compustat annual item AT) from the most recent fiscal year ending at least four months ago minus the total assets from one year prior, scaled by the 1-year-prior total assets. The left-hand side variable in the cross-sectional regressions is 1-year-ahead investment-to-assets changes, denoted $\text{d}^1\text{I/A}$, which is investment-to-assets from the first fiscal year after the most recent fiscal year end minus the current investment-to-assets. The right-hand side variables include the log of Tobin's q, $\log(q)$, operating cash flows, Cop, and the change in Roe, dRoe. At the beginning of each month t, current Tobin's q is the market equity (price per share times the number of shares outstanding from CRSP) plus long-term debt (Compustat annual item DLTT) and short-term debt (item DLC) scaled by book assets (item AT), all from the most recent fiscal year ending at least four months ago. For firms with multiple share classes, we merge the market equity for all classes. Following Ball et al. (2016), we measure Cop as total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), plus research and development expenditures (item XRD, zero if missing), minus change in accounts receivable (item RECT), minus change in inventory (item INVT), minus change in prepaid expenses (item XPP), plus change in deferred revenue (item DRC plus item DRLT), plus change in trade accounts payable (item AP), and plus change in accrued expenses (item XACC), scaled by book assets, all from the fiscal year ending at least four months ago. Missing annual changes are set to zero. Finally, dRoe is Roe minus the 4-quarter-lagged Roe, with missing dRoe values set to zero in the cross-sectional forecasting regressions. We winsorize the left- and right-hand side variables each month at the 1–99% level. To control for the impact of microcaps, we use weighted least squares with the market equity as the weights.

At the beginning of each month t, we construct the expected growth, Eg, which is the expected 1-year-ahead investment-to-assets change, by combining the most recent winsorized predictors with the average slopes estimated from the prior 120-month rolling window (30 months minimum). The most recent predictors, $\log(q)$ and Cop, in calculating Eg are from the most recent fiscal year ending at least four months ago as of month t, and dRoe is computed using the latest announced earnings, and if not available, the earnings from the most recent fiscal quarter ending at least four months ago. The average slopes in calculating Eg are estimated from the prior rolling window regressions, in which $\mathrm{d}^1\mathrm{I/A}$ is from the most recent fiscal year ending at least four months ago as of month t, and the regressors are further lagged accordingly.

B.6 Return on Assets (Roa)

Annual Roa (RoaA) is income before extraordinary items (Compustat annual item IB) divided by 1-year-lagged total assets (item AT). To form the RoaA deciles, at the end of June of year t, we sort stocks into deciles on the NYSE breakpoints of RoaA 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 $t+1$.

Quarterly return on assets, Roa, is income before extraordinary items (Compustat quarterly item IBQ) divided by 1-quarter-lagged total assets (item ATQ). At the beginning of each month t, we sort all stocks into deciles based on Roa computed with quarterly earnings from the most recent earnings announcement dates (item RDQ). For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent Roa to be within 6 months prior to the portfolio formation. We also require the earnings announcement date to be after the corresponding fiscal quarter end. Monthly decile returns are calculated for month t (Roa1), from month t to $t+5$ (Roe6), and from month t to $t+11$ (Roe12). The deciles are rebalanced at the beginning of $t+1$. Holding periods longer than one month like in Roa6 mean that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six months. We average the subdecile returns as the monthly return of the Roa6 decile. For sufficient data coverage, the Roa portfolios start in January 1972.

B.7 Operating Cash Flow-to-lagged Assets (Cla)

Annual operating cash flow-to-lagged assets, ClaA, is total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), plus research and development expenditures (item XRD, zero if missing), minus change in accounts receivable (item RECT), minus change in inventory (item INVT), minus change in prepaid expenses (item XPP), plus change in deferred revenue (item DRC plus item DRLT), plus change in trade accounts payable (item AP), and plus change in accrued expenses (item XACC), all scaled by 1-year-lagged book assets (item AT). All changes are annual changes in balance sheet items and we set missing changes to zero. At the end of June of each year t, we sort stocks into deciles based on ClaA for the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

Quarterly operating cash flow-to-lagged assets, Cla, is quarterly total revenue (Compustat quarterly item REVTQ) minus cost of goods sold (item COGSQ), minus selling, general, and administrative expenses (item XSGAQ), plus research and development expenditures (item XRDQ, zero if missing), minus change in accounts receivable (item RECTQ), minus change in inventory (item INVTQ), plus change in deferred revenue (item DRCQ plus item DRLTQ), and plus change in trade accounts payable (item APQ), all scaled by 1-quarter-lagged book assets (item ATQ). All changes are quarterly changes in balance sheet items and we set missing changes to zero.

At the beginning of each month t, we split stocks on Cla for the fiscal quarter ending at least 4 months ago. Monthly decile returns are calculated for month t (Cla1), from month t to $t+5$ (Cla6), and from month t to $t+11$ (Cla12). The deciles are rebalanced at the beginning of $t+1$. Holding periods longer than one month like in Cla6 mean that for a given decile in each month there exist 6 subdeciles, each initiated in a different month in the prior six months. We average the subdecile returns as the monthly return of the Cla6 decile. For sufficient data coverage, these portfolios start in January 1976.

B.8 Operating Profits-to-lagged Equity (Ole)

Annual operating profits-to-lagged equity (OleA) is total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS, zero if missing), minus selling, general, and administrative expenses (item XSGA, zero if missing), and minus interest expense (item XINT, zero if missing), scaled by 1-year-lagged book equity. We require at least one of the three expense items (COGS, XSGA, and XINT) to be nonmissing. Book equity is stockholders' book equity, plus balance sheet deferred taxes and investment tax credit (item TXDITC) if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat (item SEQ), if it is available. If not, we measure stockholders' equity as the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, we use redemption (item PSTKRV), liquidating (item PSTKL), or par value (item PSTK) for the book value of preferred stock. At the end of June of each year t, we sort stocks into deciles on OleA for the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

Quarterly operating profits-to-lagged equity (Ole) is quarterly total revenue (Compustat quarterly item REVTQ) minus cost of goods sold (item COGSQ, zero if missing), minus selling, general, and administrative expenses (item XSGAQ, zero if missing), and minus interest expense (item XINTQ, zero if missing), scaled by 1-quarter-lagged book equity. We require at least one of the three expense items (COGSQ, XSGAQ, and XINTQ) to be nonmissing. Book equity is shareholders' equity, plus balance sheet deferred taxes and investment tax credit (item TXDITCQ) if available, minus the book value of preferred stock (item PSTKQ). Depending on availability, we use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the book value of preferred stock, or total assets (item ATQ) minus total liabilities (item LTQ) in that order as shareholders' equity.

At the beginning of each month t, we split stocks on Ole for the fiscal quarter ending at least 4 months ago. Monthly decile returns are calculated for month t (Ole1), from month t to $t+5$ (Ole6), and from month t to $t+11$ (Ole12). The deciles are rebalanced at the beginning of $t+1$. Holding periods longer than one month like in Ole6 mean that for a given decile in each month there exist 6 subdeciles, each initiated in a different month in the prior six months. We average the subdecile returns as the monthly return of the Ole6 decile. For sufficient data coverage, these portfolios start in January 1972.

Table S1 : Buffett's Alpha, Using Compustat's Berkshire Returns Prior to September 1988, February 1968–December 2020

Prior to September 1988, we use monthly Berkshire returns from Compustat. From September 1988 onward, we mostly rely on CRSP, following the same sample construction in the main text. Panel A shows average excess return, $\overline{R}$, the q-factor alpha, the q^5 alpha, the q-factor and q^5 loadings on the market, size, investment, Roe, and expected growth factors, β_{Mkt}, β_{Me}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively, and the R-squares of the q-factor and q^5 regressions. Panel B reports the AQR 6-factor regressions of Berkshire Hathaway's excess returns. We use the QMJ factor downloaded from the AQR Web site. The t-values in the rows beneath the estimates are adjusted for heteroscedasticity and autocorrelations.

Panel A: The q-factor and q^5 regressions

Sample	$\overline{R}$	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}	R^2
2/68–12/20	1.45	0.63	0.76	−0.01	0.57	0.40		0.18
	4.96	2.38	8.54	−0.09	3.58	3.48		
		0.74	0.74	−0.03	0.60	0.45	−0.17	0.18
		2.59	8.40	−0.17	3.73	3.31	−0.96	
11/76–3/17	1.57	0.53	0.86	−0.10	0.69	0.50		0.26
	4.77	1.78	9.67	−0.78	4.06	4.65		
		0.65	0.84	−0.12	0.73	0.57	−0.20	0.26
		2.00	9.36	−0.89	4.12	4.26	−1.01	

Panel B: The AQR 6-factor regressions

Sample	α_{AQR}	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	β_{BAB}	β_{QMJ}	R^2
2/68–12/20	0.63	0.79	−0.10	0.35	0.01	0.22	0.30	0.19
	2.13	8.75	−0.67	2.62	0.20	2.25	2.03	
11/76–3/17	0.51	0.92	−0.16	0.42	−0.03	0.24	0.38	0.27
	1.75	10.03	−1.26	3.37	−0.49	2.63	2.58	

Table S2 : The Asness-Frazzini-Pedersen (2019) Alternative Quality Score (with the Payout Component) Portfolios, January 1967–December 2020

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

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

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.27	0.46	0.47	0.53	0.53	0.66	0.58	0.65	0.72	0.70	0.43	
$t_{\overline{R}}$	0.95	1.91	2.20	2.67	2.83	3.40	3.08	3.54	4.11	3.91	2.32	
α_q	−0.20	−0.05	−0.04	−0.04	−0.04	−0.06	−0.04	0.05	0.18	0.24	0.44	0.00
t_q	−1.80	−0.64	−0.42	−0.52	−0.48	−0.82	−0.66	0.82	3.25	3.51	3.22	
α_{q^5}	−0.01	0.10	0.05	−0.02	0.08	−0.05	−0.04	0.07	0.15	0.06	0.08	0.20
t_{q^5}	−0.11	1.17	0.56	−0.21	1.15	−0.63	−0.57	1.11	2.27	0.96	0.61	
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.21	−0.49	−0.25	0.51	0.54		−6.54	−10.37	−2.58	6.41	6.21	0.62

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

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.36	0.50	0.58	0.62	0.70	0.35		1.38	2.54	3.11	3.46	4.06	2.40
Micro	0.31	0.93	0.98	1.06	0.97	0.66		0.87	3.04	3.52	3.92	3.86	4.05
Small	0.57	0.80	0.80	0.92	0.96	0.40		1.82	3.18	3.32	3.79	4.10	2.94
Big	0.37	0.48	0.55	0.60	0.69	0.32		1.50	2.47	3.03	3.37	3.99	2.31
			α_q ($p_{\mathrm{GRS}}=0.00$)							t_q			
All	−0.13	−0.04	−0.05	0.02	0.21	0.34		−1.63	−0.64	−0.99	0.43	4.45	3.45
Micro	−0.15	0.24	0.23	0.31	0.27	0.42		−0.90	2.00	1.86	2.99	2.52	3.27
Small	0.00	0.09	−0.02	0.12	0.20	0.20		−0.02	1.48	−0.19	1.95	2.26	1.75
Big	−0.07	−0.03	−0.06	0.01	0.21	0.28		−0.79	−0.50	−0.95	0.23	4.27	2.59
			α_{q^5} ($p_{\mathrm{GRS}}=0.00$)							t_{q^5}			
All	0.03	0.00	0.02	0.03	0.09	0.05		0.44	0.08	0.33	0.55	1.84	0.56
Micro	−0.07	0.36	0.26	0.36	0.26	0.33		−0.39	2.61	2.27	3.72	2.44	2.50
Small	0.12	0.16	0.03	0.16	0.20	0.08		1.50	2.55	0.41	2.64	2.54	0.77
Big	0.09	0.01	0.02	0.02	0.08	−0.01		1.01	0.12	0.32	0.39	1.67	−0.12
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	−0.15	−0.39	−0.18	0.40	0.43		−5.77	−10.16	−2.57	6.75	6.55		0.65
Micro	−0.22	−0.18	0.20	0.65	0.14		−7.22	−3.92	2.29	7.81	1.82		0.52
Small	−0.21	−0.15	0.21	0.54	0.17		−6.00	−1.73	2.59	6.11	2.18		0.50
Big	−0.13	−0.25	−0.20	0.37	0.44		−4.35	−6.35	−2.60	5.81	6.05		0.51

Table S3 : The Asness-Frazzini-Pedersen (2019) Profitability Score Portfolios, January 1967–December 2020

The profitability score is detailed in the Internet Appendix. In Panel A, at the beginning of each month t, we sort stocks into deciles based on the NYSE breakpoints of the profitability score. To align the timing between component signals and subsequent returns, we assume that accounting variables in fiscal year ending in calendar year $y-1$ are publicly known at the June-end of year y. 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 profitability 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 profitability sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

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

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.39	0.53	0.52	0.51	0.56	0.48	0.61	0.62	0.60	0.75	0.36	
$t_{\overline{R}}$	1.47	2.49	2.63	2.58	2.90	2.41	3.26	3.37	3.24	3.99	2.01	
α_q	0.00	0.01	−0.07	−0.08	−0.07	−0.06	−0.01	0.03	0.06	0.27	0.27	0.02
t_q	0.00	0.14	−0.93	−1.10	−0.85	−0.78	−0.09	0.50	0.99	3.78	2.06	
α_{q^5}	0.14	0.13	0.04	0.01	−0.01	0.10	−0.02	0.03	−0.01	0.10	−0.04	0.25
t_{q^5}	1.29	1.29	0.53	0.08	−0.14	1.20	−0.27	0.40	−0.16	1.37	−0.30	
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.08	−0.46	−0.30	0.60	0.46		−2.25	−9.39	−3.87	8.05	4.82	0.56

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

	L	2	3	4	H	H−L	L	2	3	4	H	H−L
			$\overline{R}$						$t_{\overline{R}}$			
All	0.45	0.52	0.51	0.61	0.69	0.24	1.94	2.69	2.70	3.39	3.77	1.82
Micro	0.42	0.78	0.97	1.04	1.06	0.63	1.23	2.57	3.38	3.62	3.78	4.54
Small	0.61	0.70	0.82	0.89	1.01	0.40	2.08	2.90	3.27	3.52	3.97	3.14
Big	0.47	0.51	0.49	0.58	0.67	0.20	2.16	2.69	2.63	3.30	3.71	1.53
			α_q ($p_{\mathrm{GRS}} = 0.00$)						t_q			
All	0.00	−0.06	−0.08	0.01	0.19	0.19	0.02	−1.12	−1.33	0.15	3.52	1.85
Micro	0.00	0.11	0.24	0.23	0.30	0.30	−0.02	0.85	2.08	2.09	2.79	2.22
Small	0.13	−0.04	0.04	0.05	0.20	0.08	1.67	−0.53	0.50	0.61	2.73	0.66
Big	0.05	−0.04	−0.09	0.00	0.19	0.14	0.53	−0.76	−1.32	0.03	3.43	1.18
			α_{q^5} ($p_{\mathrm{GRS}} = 0.00$)						t_{q^5}			
All	0.12	0.03	0.02	0.00	0.05	−0.08	1.46	0.54	0.40	−0.01	0.87	−0.77
Micro	0.06	0.21	0.33	0.30	0.32	0.26	0.35	1.86	2.96	2.78	3.14	1.77
Small	0.20	0.06	0.09	0.10	0.20	0.00	2.60	0.85	1.37	1.51	2.67	0.01
Big	0.18	0.05	0.02	−0.01	0.05	−0.13	1.67	0.73	0.36	−0.11	0.80	−1.09

	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}	t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
All	−0.03	−0.33	−0.32	0.41	0.40	−1.00	−9.25	−5.39	7.07	5.45	0.56
Micro	−0.05	−0.05	0.14	0.63	0.07	−1.50	−0.86	1.41	7.55	0.68	0.33
Small	−0.05	−0.01	0.08	0.62	0.11	−1.60	−0.13	0.88	7.19	1.30	0.37
Big	−0.01	−0.21	−0.36	0.37	0.41	−0.30	−4.97	−5.15	5.34	4.94	0.40

Table S4 : The Asness-Frazzini-Pedersen (2019) Growth Score Portfolios, January 1967–December 2020

In Panel A, at the beginning of each month t, we sort stocks into deciles based on the NYSE breakpoints of the growth score. To align the timing between component signals and subsequent returns, we assume that accounting variables in fiscal year ending in calendar year $y-1$ are publicly known at the June-end of year y. 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 growth 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 growth score sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

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

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.46	0.48	0.64	0.61	0.56	0.60	0.63	0.60	0.63	0.71	0.25	
$t_{\overline{R}}$	2.02	2.63	3.59	3.57	3.36	3.47	3.47	3.43	3.48	3.27	1.49	
α_q	−0.13	−0.19	−0.12	−0.02	0.00	−0.06	−0.05	−0.04	0.00	0.35	0.48	0.00
t_q	−1.40	−1.85	−1.56	−0.24	0.02	−0.76	−0.66	−0.56	0.00	4.14	3.76	
α_{q^5}	−0.14	−0.20	−0.11	−0.06	−0.02	0.01	−0.01	−0.01	0.05	0.19	0.33	0.44
t_{q^5}	−1.37	−1.87	−1.32	−0.67	−0.33	0.08	−0.09	−0.19	0.62	2.31	2.40	
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	0.01	−0.36	−1.08	0.37	0.23		0.20	−6.40	−11.93	4.44	2.30	0.43

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

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.47	0.62	0.57	0.62	0.68	0.21		2.43	3.67	3.45	3.59	3.42	1.54
Micro	0.75	0.98	1.02	1.09	0.93	0.18		2.43	3.66	3.73	3.95	3.21	1.69
Small	0.74	0.87	0.95	0.92	0.92	0.18		2.78	3.88	4.13	3.86	3.52	1.68
Big	0.45	0.60	0.55	0.61	0.67	0.21		2.43	3.62	3.36	3.56	3.38	1.52
			α_q ($p_{\mathrm{GRS}}=0.00$)							t_q			
All	−0.17	−0.07	−0.03	−0.03	0.24	0.41		−2.12	−1.08	−0.61	−0.63	3.96	3.72
Micro	0.07	0.22	0.22	0.32	0.22	0.15		0.58	2.38	1.87	2.94	2.22	1.54
Small	−0.02	0.03	0.14	0.04	0.15	0.16		−0.17	0.48	1.38	0.52	1.84	1.56
Big	−0.16	−0.07	−0.04	−0.03	0.24	0.40		−1.81	−1.00	−0.71	−0.58	3.94	3.41
			α_{q^5} ($p_{\mathrm{GRS}}=0.02$)							t_{q^5}			
All	−0.18	−0.08	−0.02	0.00	0.14	0.31		−2.09	−1.18	−0.45	−0.07	2.25	2.77
Micro	0.13	0.26	0.28	0.37	0.19	0.06		1.03	2.79	2.59	3.59	1.93	0.59
Small	0.05	0.08	0.17	0.07	0.16	0.11		0.47	1.04	1.91	0.98	2.04	0.96
Big	−0.18	−0.08	−0.03	0.00	0.14	0.32		−1.90	−1.09	−0.52	−0.04	2.24	2.58
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	0.02	−0.21	−0.98	0.31	0.14		0.67	−4.97	−12.30	4.17	1.72		0.46
Micro	−0.01	0.01	−0.39	0.29	0.14		−0.45	0.30	−5.41	5.61	1.81		0.20
Small	−0.06	0.06	−0.47	0.36	0.08		−1.89	1.39	−7.23	5.74	1.17		0.25
Big	0.04	−0.16	−1.00	0.30	0.12		0.96	−3.67	−11.50	3.82	1.45		0.42

Table S5 : The Asness-Frazzini-Pedersen (2019) Safety Score Portfolios, January 1967–December 2020

In Panel A, at the beginning of each month t, we sort stocks into deciles based on the NYSE breakpoints of the safety score. To align the timing between component signals and subsequent returns, we assume 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 safety 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 safety score sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 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 portfolios are jointly zero.

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

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.45	0.60	0.63	0.52	0.56	0.59	0.64	0.70	0.64	0.57	0.12	
$t_{\overline{R}}$	1.43	2.28	2.81	2.49	3.08	3.15	3.52	3.81	3.49	3.37	0.54	
α_q	−0.24	−0.01	0.04	−0.08	0.02	0.07	0.09	0.14	0.16	0.07	0.31	0.00
t_q	−1.99	−0.12	0.56	−1.05	0.30	1.01	1.42	2.30	2.45	1.14	1.99	
α_{q^5}	−0.06	0.19	0.14	−0.01	0.01	0.08	0.03	0.12	0.02	0.03	0.09	0.19
t_{q^5}	−0.54	1.55	1.71	−0.16	0.18	1.06	0.42	1.72	0.31	0.41	0.58	
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.44	−0.48	−0.26	0.46	0.33		−9.33	−7.42	−2.51	4.53	3.45	0.59

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

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.53	0.56	0.56	0.67	0.61	0.08		1.89	2.62	3.13	3.75	3.57	0.43
Micro	0.50	0.91	0.86	0.97	0.82	0.33		1.33	2.92	3.03	3.58	3.36	1.94
Small	0.68	0.84	0.83	0.93	0.83	0.15		2.13	3.26	3.34	3.86	3.64	1.08
Big	0.54	0.53	0.54	0.66	0.60	0.06		1.97	2.51	3.09	3.71	3.55	0.35
			α_q ($p_{\mathrm{GRS}} = 0.00$)							t_q			
All	−0.11	−0.03	0.04	0.12	0.12	0.22		−1.06	−0.46	0.70	2.70	2.43	1.72
Micro	−0.06	0.29	0.13	0.29	0.21	0.27		−0.41	2.46	1.09	2.30	1.67	2.31
Small	−0.02	0.09	0.11	0.16	0.16	0.19		−0.30	1.20	1.64	2.19	2.19	1.72
Big	−0.07	−0.04	0.04	0.12	0.12	0.19		−0.58	−0.52	0.72	2.60	2.36	1.29
			α_{q^5} ($p_{\mathrm{GRS}} = 0.00$)							t_{q^5}			
All	0.09	0.06	0.03	0.08	0.02	−0.08		0.90	0.99	0.58	1.59	0.36	−0.62
Micro	0.03	0.39	0.19	0.31	0.23	0.20		0.19	2.82	1.66	2.55	1.82	1.74
Small	0.12	0.17	0.18	0.15	0.17	0.05		1.68	2.14	2.57	2.19	2.29	0.51
Big	0.15	0.05	0.03	0.08	0.02	−0.13		1.18	0.84	0.56	1.55	0.31	−0.92
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	−0.30	−0.38	−0.30	0.34	0.45		−8.37	−6.52	−4.07	4.26	5.26		0.59
Micro	−0.32	−0.29	0.01	0.62	0.10		−9.20	−6.09	0.12	9.03	1.31		0.57
Small	−0.30	−0.23	−0.08	0.41	0.20		−8.56	−3.12	−0.98	4.61	2.58		0.51
Big	−0.30	−0.21	−0.30	0.27	0.49		−7.30	−3.69	−3.72	3.26	5.00		0.45

Table S6 : The Asness-Frazzini-Pedersen (2019) Payout Score Portfolios, January 1967–December 2020

In Panel A, at the beginning of each month t, we sort stocks into deciles based on the NYSE breakpoints of the payout score. To align the timing between component signals and subsequent returns, we assume that accounting variables in fiscal year ending in calendar year $y-1$ are publicly known at the June-end of year y. 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 payout 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 payout score sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 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 portfolios are jointly zero.

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

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.35	0.65	0.54	0.52	0.61	0.67	0.62	0.74	0.60	0.75	0.41	
$t_{\overline{R}}$	1.31	2.87	2.55	2.56	3.33	3.86	3.52	4.51	3.74	4.49	2.43	
α_q	−0.04	0.26	0.11	0.01	0.02	0.04	−0.01	0.06	−0.04	0.02	0.06	0.12
t_q	−0.47	2.65	1.50	0.08	0.25	0.58	−0.22	0.87	−0.59	0.37	0.59	
α_{q^5}	0.02	0.23	0.10	−0.03	0.08	0.05	−0.04	−0.05	−0.10	−0.10	−0.12	0.27
t_{q^5}	0.22	2.41	1.29	−0.47	0.87	0.75	−0.52	−0.66	−1.48	−1.39	−0.92	
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.13	−0.20	1.04	0.17	0.27		−4.69	−3.98	16.13	2.88	3.25	0.56

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

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.50	0.53	0.63	0.66	0.67	0.17		2.12	2.63	3.62	4.03	4.22	1.22
Micro	0.39	0.90	1.05	1.17	1.07	0.69		1.13	2.92	3.66	4.11	4.26	4.47
Small	0.60	0.90	0.95	0.93	0.95	0.35		2.05	3.45	3.90	4.03	4.43	2.42
Big	0.54	0.51	0.61	0.64	0.65	0.11		2.32	2.56	3.52	3.94	4.11	0.82
			α_q ($p_{\mathrm{GRS}} = 0.00$)							t_q			
All	0.14	0.07	0.02	0.01	−0.01	−0.15		1.91	1.25	0.40	0.12	−0.15	−1.59
Micro	−0.11	0.22	0.22	0.36	0.25	0.36		−0.74	1.88	2.03	2.50	2.59	2.69
Small	0.02	0.16	0.05	0.02	0.09	0.07		0.33	2.70	0.81	0.24	1.02	0.62
Big	0.21	0.07	0.02	0.00	−0.02	−0.22		2.60	1.29	0.35	−0.01	−0.34	−2.30
			α_{q^5} ($p_{\mathrm{GRS}} = 0.00$)							t_{q^5}			
All	0.14	0.04	0.06	−0.08	−0.10	−0.24		1.97	0.67	1.05	−1.44	−1.89	−2.54
Micro	−0.04	0.31	0.27	0.55	0.27	0.32		−0.30	2.55	2.58	2.37	2.94	2.31
Small	0.10	0.18	0.13	0.09	0.09	−0.01		1.36	2.82	2.00	1.31	1.14	−0.09
Big	0.20	0.03	0.06	−0.08	−0.11	−0.31		2.54	0.58	0.97	−1.55	−2.00	−3.05
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	−0.10	−0.17	0.94	0.18	0.14		−4.88	−4.21	16.20	3.30	2.03		0.59
Micro	−0.20	−0.13	0.73	0.46	0.06		−5.74	−3.14	8.52	4.60	0.68		0.52
Small	−0.20	−0.21	0.95	0.24	0.11		−5.89	−2.96	11.60	2.59	1.32		0.60
Big	−0.09	−0.11	0.97	0.15	0.13		−4.01	−2.54	15.74	2.84	1.76		0.54

Table S7 : The Bartram-Grinblatt (2015, 2018) Agnostic Fundamental Portfolios, with the \$5 Price Screen, January 1977–December 2020

The agnostic measure, $(V-P)/P$, 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}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

Panel A: Deciles from one-way agnostic sorts

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.59	0.73	0.59	0.66	0.82	0.85	0.89	0.90	0.96	1.12	0.53	
$t_{\overline{R}}$	2.20	3.05	3.03	3.82	4.15	4.23	3.86	3.84	3.59	3.84	2.75	
α_q	−0.01	0.07	−0.06	0.12	0.14	0.15	0.12	0.08	0.12	0.26	0.27	0.10
t_q	−0.10	0.54	−0.82	1.33	1.65	1.56	0.82	0.63	0.77	1.59	1.30	
α_{q^5}	0.11	−0.01	−0.11	0.06	0.09	0.19	0.22	0.19	0.26	0.42	0.31	0.07
t_{q^5}	0.87	−0.06	−1.57	0.56	0.95	2.00	1.47	1.52	1.87	3.08	1.66	
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	0.00	0.39	0.67	−0.03	−0.07		0.02	3.43	5.17	−0.23	−0.48	0.19

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	0.72	0.63	0.82	0.89	1.02	0.29	2.96	3.53	4.32	3.93	3.75	1.43
Micro	0.43	0.66	0.78	0.87	1.14	0.71	1.17	1.70	2.48	3.04	4.13	3.15
Small	0.66	0.90	0.87	1.04	1.08	0.43	2.00	3.26	3.31	3.99	3.75	2.10
Big	0.75	0.63	0.83	0.89	1.03	0.28	3.09	3.57	4.42	3.96	3.75	1.24
			α_q ($p_{\mathrm{GRS}}=0.00$)						t_q			
All	0.10	0.05	0.14	0.11	0.17	0.07	0.87	0.81	2.02	0.84	1.10	0.29
Micro	−0.14	−0.07	−0.10	−0.08	0.23	0.37	−0.75	−0.23	−0.54	−0.58	1.72	1.62
Small	0.00	0.07	−0.02	0.10	0.14	0.14	−0.04	0.86	−0.22	0.91	0.93	0.61
Big	0.14	0.06	0.16	0.16	0.28	0.13	1.19	0.96	2.30	1.06	1.49	0.48
			α_{q^5} ($p_{\mathrm{GRS}}=0.00$)						t_{q^5}			
All	0.07	−0.03	0.12	0.22	0.31	0.24	0.74	−0.47	1.67	1.66	2.41	1.15
Micro	−0.12	0.21	−0.16	−0.09	0.34	0.47	−0.64	0.51	−0.78	−0.72	2.99	2.17
Small	0.04	0.08	0.02	0.18	0.28	0.24	0.35	0.79	0.18	1.75	2.25	1.21
Big	0.13	−0.02	0.14	0.27	0.40	0.27	1.16	−0.36	1.85	1.80	2.38	1.08

	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}	t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
All	0.06	0.34	0.75	−0.14	−0.26	0.86	1.66	4.06	−0.81	−1.72	0.22
Micro	−0.03	−0.15	0.57	0.48	−0.15	−0.47	−1.52	3.70	3.21	−0.93	0.15
Small	0.01	−0.30	0.98	0.19	−0.16	0.16	−1.76	5.74	0.96	−0.93	0.23
Big	0.10	0.13	0.66	−0.22	−0.21	1.45	0.66	3.54	−1.22	−1.26	0.13

Table S8 : The Penman-Zhang (2020a) Accounting Factors, NYSE-Amex-NASDAQ Breakpoints and Equal-weighted Returns

Section 4.9 details earnings-to-price (E/P), return on equity (RoeA), and expensed investment-to-lagged price (ExpInv/P). Panel A shows the $4 \times 3 \times 3$ portfolios from sequential sorts on E/P, RoeA, and ExpInv/P. At the end of June of year t, we split stocks into 4 E/P groups based on negative E/P and NYSE-Amex-NASDAQ breakpoints of positive E/P. Within each E/P portfolio, we split stocks into RoeA terciles on its NYSE-Amex-NASDAQ breakpoints. Within each E/P-RoeA portfolio, we split stocks into ExpInv/P terciles on its NYSE-Amex-NASDAQ breakpoints. Monthly equal-weighted returns are from July of year t to June of $t+1$, and the portfolios are rebalanced in June-end of $t+1$. The SUM factor is the high E/P-low RoeA-high ExpInv/P portfolio minus the low E/P-high RoeA-low ExpInv/P portfolio. Columns denoted "Col. 3−7" show the results for the Low RoeA-High ExpInv/P portfolio minus the high RoeA-low ExpInv/P portfolio. In Panel B, the Penman-Zhang investment factor (INV) is the equal-weighted high-minus-low tercile returns from annual one-way sorts on the NYSE-Amex-NASDAQ breakpoints of INV/P (change in total assets scaled by lagged market equity). All t-values are adjusted for autocorrelations and heteroscedasticity.

Panel A: The Penman-Zhang $4 \times 3 \times 3$ benchmark portfolios on E/P, annual Roe, and ExpInv/P

RoeA	Low	Low	Low	M	M	M	High	High	High	Col.	Low	Low	Low	M	M	M	High	High	High	Col.
ExpInv/P	Low	M	High	Low	M	High	Low	M	High	3−7	Low	M	High	Low	M	High	Low	M	High	3−7
	Average excess returns, $\overline{R}$										$t_{\overline{R}}$									
E/P<0	0.44	0.55	0.85	0.59	1.13	1.34	0.79	1.19	1.33	0.06	0.92	1.18	1.84	1.49	2.87	3.34	2.37	3.62	3.80	0.21
Low E/P	0.55	1.06	1.30	0.41	0.60	0.91	0.37	0.56	0.64	0.92	2.02	3.50	4.20	1.61	2.25	3.15	1.44	2.09	2.18	5.30
M	0.75	1.04	1.28	0.65	0.89	1.01	0.67	0.80	0.89	0.60	4.09	4.03	4.73	3.40	4.04	4.08	2.97	3.24	3.43	4.54
High E/P	1.02	1.01	1.42	0.87	1.13	1.14	0.80	1.03	1.26	0.62	4.88	3.97	4.78	4.10	4.71	4.45	3.07	3.80	4.13	4.10
SUM										1.04										5.17
	The q-factor alpha, α_q ($p_{\mathrm{GRS}} = 0.00$)										t_q									
E/P<0	0.18	0.37	0.67	0.31	0.74	0.95	0.16	0.70	0.75	0.50	0.59	1.29	2.16	1.38	3.41	3.79	1.03	3.94	3.42	1.62
Low E/P	−0.13	0.40	0.63	−0.09	0.02	0.33	−0.17	−0.06	0.02	0.80	−0.92	3.05	4.25	−0.74	0.15	2.36	−1.75	−0.63	0.17	4.92
M	0.07	0.26	0.53	−0.07	0.10	0.20	−0.01	0.07	0.12	0.54	0.68	2.34	4.24	−0.74	1.25	1.69	−0.07	0.65	1.01	3.92
High E/P	0.33	0.21	0.68	0.24	0.38	0.35	0.12	0.26	0.44	0.56	2.52	1.74	4.51	1.80	3.59	2.86	0.86	2.16	2.85	3.68
SUM										0.85										4.79
	The q^5 alpha, α_{q^5} ($p_{\mathrm{GRS}} = 0.00$)										t_{q^5}									
E/P<0	0.08	0.16	0.59	0.37	0.59	0.83	0.40	0.63	0.70	0.19	0.26	0.55	1.91	1.59	2.69	3.16	2.21	3.31	3.09	0.59
Low E/P	0.07	0.36	0.60	0.08	0.08	0.40	−0.01	−0.03	0.14	0.60	0.50	2.62	3.98	0.62	0.65	2.86	−0.09	−0.36	0.94	3.56
M	0.14	0.28	0.52	−0.01	0.08	0.25	0.03	0.10	0.17	0.50	1.27	2.82	4.12	−0.11	0.97	2.22	0.29	1.08	1.43	3.19
High E/P	0.44	0.24	0.63	0.30	0.40	0.39	0.16	0.25	0.45	0.47	3.42	1.96	4.40	2.35	3.97	3.32	1.27	2.30	3.19	2.89
SUM										0.64										3.41

Panel B: Factor spanning tests between the Penman-Zhang 3-factor model and the q models

	$\overline{R}$	α	β_{Mkt}	β_{SUM}	β_{INV}	R^2
R_{Me}	0.27	−0.19	0.23	0.19	−0.24	0.21
[t]	2.22	−1.56	7.85	5.71	−1.65	
$R_{\mathrm{I/A}}$	0.33	0.19	−0.12	0.15	−0.12	0.30
[t]	4.10	2.49	−6.58	7.76	−1.39	
R_{Roe}	0.51	0.94	−0.16	−0.11	0.42	0.24
[t]	4.96	10.49	−4.88	−2.71	6.49	
R_{Eg}	0.80	0.98	−0.21	−0.00	0.09	0.23
[t]	9.69	13.03	−8.42	−0.01	2.25	

	$\overline{R}$	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}	R^2
SUM	1.04	0.85	−0.17	0.45	1.06	−0.36		0.37
[t]	5.17	4.79	−3.78	6.80	8.89	−3.25		
		0.64	−0.14	0.48	1.00	−0.47	0.32	0.38
[t]		3.41	−2.95	7.20	8.14	−3.71	2.29	
INV	−0.53	−0.57	0.04	−0.12	−0.28	0.28		0.25
[t]	−5.42	−5.16	1.55	−2.09	−3.93	5.56		
		−0.49	0.03	−0.13	−0.26	0.32	−0.12	0.25
[t]		−5.37	1.17	−2.18	−3.33	5.12	−1.84	

Table S9 : The Penman-Zhang (2020a) Accounting-based Factors, Alternative ExpInv without SG&A

Section 4.9 details earnings-to-price (E/P), return on equity (RoeA), and expensed investment-to-lagged price (ExpInv/P). This table shows the results with an alternative ExpInv without SG&A. Panel A shows the $4 \times 3 \times 3$ portfolios from sequential sorts on E/P, RoeA, and ExpInv/P. At the end of June of each year t, we split stocks into 4 E/P groups based on negative E/P and NYSE breakpoints of positive E/P. Within each E/P portfolio, we split stocks into RoeA terciles on NYSE breakpoints. Within each E/P-RoeA portfolio, we split stocks into ExpInv/P terciles based on NYSE breakpoints. Monthly value-weighted returns are from July of year t to June of $t+1$, and the portfolios are rebalanced in June-end of $t+1$. The SUM factor is the high E/P-low RoeA-high ExpInv/P portfolio minus the low E/P-high RoeA-low ExpInv/P portfolio. Columns denoted "Col. 3−7" show the results for the Low RoeA-High ExpInv/P portfolio minus the high RoeA-low ExpInv/P portfolio. In Panel B, the Penman-Zhang investment factor (INV) is the value-weighted high-minus-low tercile returns from annual one-way sorts on the NYSE breakpoints of INV/P (change in total assets scaled by lagged market equity). All t-values are adjusted for autocorrelations and heteroscedasticity.

Panel A: The Penman-Zhang $4 \times 3 \times 3$ benchmark portfolios on E/P, annual Roe, and ExpInv/P

RoeA	Low	Low	Low	M	M	M	High	High	High	Col.
ExpInv/P	Low	M	High	Low	M	High	Low	M	High	3−7
	Average excess returns, $\overline{R}$									
E/P<0	−0.15	0.07	0.87	0.39	0.68	0.93	0.85	0.86	0.57	0.02
Low E/P	0.48	0.43	0.60	0.32	0.53	0.65	0.45	0.48	0.74	0.14
M	0.56	0.45	0.76	0.45	0.61	0.82	0.59	0.67	0.76	0.16
High E/P	0.76	0.84	0.90	0.60	0.92	0.97	0.75	0.90	0.79	0.16
SUM										0.45
	The q-factor alpha, α_q ($p_{\mathrm{GRS}} = 0.00$)									
E/P<0	−0.79	−0.12	0.54	−0.38	−0.22	0.33	0.06	0.08	0.05	0.48
Low E/P	−0.18	−0.38	0.03	−0.35	−0.15	0.14	−0.23	−0.02	0.24	0.26
M	−0.11	−0.26	−0.02	−0.28	−0.17	0.12	−0.23	0.01	0.08	0.22
High E/P	0.00	0.30	0.18	0.05	0.10	0.26	−0.10	0.10	0.17	0.28
SUM										0.42
	The q^5 alpha, α_{q^5} ($p_{\mathrm{GRS}} = 0.00$)									
E/P<0	−0.40	−0.08	0.26	0.01	−0.23	−0.03	0.40	0.28	−0.15	−0.14
Low E/P	−0.00	−0.33	−0.10	−0.15	−0.02	0.05	−0.01	−0.07	0.12	−0.09
M	−0.06	−0.28	−0.11	−0.15	−0.15	0.07	−0.21	−0.02	−0.07	0.10
High E/P	0.08	0.30	0.17	0.16	0.22	0.08	0.04	0.05	0.04	0.13
SUM										0.19

RoeA	Low	Low	Low	M	M	M	High	High	High	Col.
ExpInv/P	Low	M	High	Low	M	High	Low	M	High	3−7
	$t_{\overline{R}}$									
E/P<0	−0.38	0.14	2.23	1.21	1.82	2.38	2.81	2.44	1.59	0.06
Low E/P	2.19	1.80	2.28	1.50	2.44	2.96	1.99	2.13	3.61	0.84
M	3.45	1.70	3.52	2.54	2.86	4.28	2.91	3.33	3.90	1.00
High E/P	4.17	2.56	3.73	3.39	4.21	4.37	3.13	4.06	3.50	0.88
SUM										2.51
	t_q									
E/P<0	−3.15	−0.40	2.19	−1.69	−0.82	1.29	0.27	0.37	0.18	1.51
Low E/P	−1.36	−2.59	0.19	−2.81	−1.21	1.19	−2.35	−0.25	2.46	1.60
M	−0.97	−1.42	−0.14	−2.69	−1.46	1.08	−2.14	0.11	0.76	1.29
High E/P	0.00	1.27	1.27	0.45	0.62	2.00	−0.63	0.63	1.15	1.32
SUM										2.72
	t_{q^5}									
E/P<0	−1.58	−0.23	1.01	0.03	−0.80	−0.12	1.71	1.14	−0.54	−0.41
Low E/P	−0.02	−2.16	−0.65	−1.18	−0.15	0.46	−0.13	−0.71	1.17	−0.50
M	−0.53	−1.32	−0.79	−1.33	−1.26	0.62	−1.83	−0.15	−0.61	0.58
High E/P	0.53	1.19	1.17	1.21	1.40	0.59	0.26	0.31	0.31	0.57
SUM										1.13

Panel B: Factor spanning tests between the Penman-Zhang 3-factor model and the q models

	$\overline{R}$	α	β_{Mkt}	β_{SUM}	β_{INV}	R^2
R_{Me}	0.27	0.11	0.16	0.24	0.25	0.21
[t]	2.22	1.00	6.00	5.97	3.91	
$R_{\mathrm{I/A}}$	0.33	0.29	−0.10	0.13	−0.34	0.42
[t]	4.10	4.48	−5.20	6.99	−6.70	
R_{Roe}	0.51	0.68	−0.12	−0.27	−0.13	0.26
[t]	4.96	7.96	−3.71	−8.98	−1.84	
R_{Eg}	0.80	0.92	−0.19	−0.04	−0.11	0.25
[t]	9.69	13.40	−8.82	−2.26	−2.10	

	$\overline{R}$	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}	R^2
SUM	0.45	0.42	−0.04	0.34	0.83	−0.63		0.36
[t]	2.51	2.72	−0.89	6.20	8.28	−8.47		
		0.19	0.00	0.38	0.76	−0.74	0.35	0.38
[t]		1.13	0.06	7.01	7.49	−8.16	3.52	
INV	−0.13	0.07	0.02	0.11	−0.61	−0.07		0.31
[t]	−1.34	0.79	0.47	2.36	−7.76	−1.26		
		0.05	0.02	0.11	−0.62	−0.09	0.04	0.31
[t]		0.49	0.64	2.23	−8.74	−1.47	0.47	

Table S10 : The Penman-Zhang (2020a) Accounting-based Factors, with Operating Cash Flow-to-price (Cop/P)

Section 4.9 details operating cash flow-to-price (Cop/P), return on equity (RoeA), and expensed investment-to-lagged price (ExpInv/P). Panel A shows the $4 \times 3 \times 3$ portfolios from sequential sorts on Cop/P, RoeA, and ExpInv/P. At the end of June of each year t, we split stocks into 4 Cop/P groups based on negative Cop/P and NYSE breakpoints of positive Cop/P. Within each Cop/P portfolio, we split stocks into RoeA terciles on NYSE breakpoints. Within each Cop/P-RoeA portfolio, we split stocks into ExpInv/P terciles based on NYSE breakpoints. Monthly value-weighted returns are from July of year t to June of $t+1$, and the portfolios are rebalanced in June-end of $t+1$. The SUM factor is the high Cop/P-low RoeA-high ExpInv/P portfolio minus the low Cop/P-high RoeA-low ExpInv/P portfolio. Columns denoted "Col. 3−7" show the results for the Low RoeA-High ExpInv/P portfolio minus the high RoeA-low ExpInv/P portfolio. In Panel B, the Penman-Zhang investment factor (INV) is the value-weighted high-minus-low tercile returns from annual one-way sorts on the NYSE breakpoints of INV/P (change in total assets scaled by lagged market equity). All t-values are adjusted for autocorrelations and heteroscedasticity.

Panel A: The Penman-Zhang $4 \times 3 \times 3$ benchmark portfolios on Cop/P, annual Roe, and ExpInv/P

RoeA	Low	Low	Low	M	M	M	High	High	High	Col.	Low	Low	Low	M	M	M	High	High	High	Col.
ExpInv/P	Low	M	High	Low	M	High	Low	M	High	3−7	Low	M	High	Low	M	High	Low	M	High	3−7
	Average excess returns, $\overline{R}$										$t_{\overline{R}}$									
Cop/P<0	−0.49	0.27	0.48	0.14	0.17	0.77	−0.17	0.26	0.66	0.65	−1.18	0.65	1.14	0.48	0.47	1.97	−0.50	0.71	1.59	1.92
Low Cop/P	0.32	0.49	0.81	0.35	0.50	0.66	0.38	0.61	0.70	0.43	1.25	2.01	2.86	1.72	2.40	3.25	1.55	3.07	3.19	2.34
M	0.58	0.54	0.81	0.53	0.73	0.88	0.71	0.84	1.02	0.10	2.56	2.47	3.33	2.53	3.51	3.73	3.85	4.17	5.04	0.61
High Cop/P	0.68	1.01	0.96	0.67	0.95	1.07	0.78	0.86	0.87	0.18	2.42	3.53	3.08	3.09	4.47	4.39	3.59	3.81	3.67	0.76
SUM										0.59										2.33
	The q-factor alpha, α_q ($p_{\mathrm{GRS}} = 0.00$)										t_q									
Cop/P<0	−0.98	−0.04	0.28	−0.38	−0.71	−0.24	−0.87	−0.41	−0.03	1.15	−3.46	−0.13	0.88	−1.86	−2.87	−0.83	−3.70	−1.69	−0.09	2.83
Low Cop/P	−0.23	0.05	0.43	−0.30	−0.02	0.07	−0.02	0.07	0.11	0.45	−1.47	0.40	2.96	−2.69	−0.21	0.62	−0.16	0.75	1.15	2.40
M	−0.18	−0.18	0.01	−0.18	0.04	0.15	0.08	0.05	0.24	−0.08	−1.25	−1.52	0.06	−1.50	0.30	0.90	0.78	0.43	2.25	−0.49
High Cop/P	−0.22	0.34	0.11	−0.05	0.13	0.31	0.01	0.13	0.11	0.10	−1.23	1.91	0.72	−0.32	0.98	2.13	0.07	0.87	0.84	0.44
SUM										0.13										0.73
	The q^5 alpha, α_{q^5} ($p_{\mathrm{GRS}} = 0.11$)										t_{q^5}									
Cop/P<0	−0.52	0.09	0.26	−0.16	−0.38	−0.11	−0.51	−0.14	−0.01	0.78	−1.76	0.35	0.78	−0.71	−1.72	−0.39	−1.96	−0.56	−0.05	1.70
Low Cop/P	0.13	0.13	0.38	−0.09	0.05	0.19	−0.02	0.06	0.13	0.40	0.82	1.02	2.37	−0.82	0.46	1.57	−0.16	0.59	1.18	2.01
M	−0.06	−0.26	−0.06	−0.19	0.01	0.02	0.06	−0.05	0.05	−0.12	−0.40	−2.15	−0.45	−1.55	0.04	0.12	0.51	−0.42	0.40	−0.69
High Cop/P	−0.08	0.07	−0.12	0.09	0.06	0.22	0.04	0.07	0.04	−0.17	−0.42	0.43	−0.74	0.55	0.39	1.47	0.27	0.49	0.33	−0.66
SUM										−0.10										−0.53

Panel B: Factor spanning tests between the Penman-Zhang 3-factor model and the q models

	$\overline{R}$	α	β_{Mkt}	β_{SUM}	β_{INV}	R^2
R_{Me}	0.27	0.06	0.12	0.28	0.19	0.40
[t]	2.22	0.70	4.94	10.13	3.73	
$R_{\mathrm{I/A}}$	0.33	0.29	−0.12	0.11	−0.37	0.45
[t]	4.10	4.52	−5.38	8.83	−7.45	
R_{Roe}	0.51	0.65	−0.09	−0.17	−0.08	0.20
[t]	4.96	7.53	−2.63	−7.97	−1.01	
R_{Eg}	0.80	0.92	−0.19	−0.04	−0.10	0.25
[t]	9.69	13.48	−8.63	−2.73	−1.89	

	$\overline{R}$	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}	R^2
SUM	0.59	0.13	0.08	1.02	1.21	−0.53		0.52
[t]	2.33	0.73	1.56	16.26	11.28	−5.94		
		−0.10	0.12	1.05	1.14	−0.65	0.34	0.53
[t]		−0.53	2.29	16.59	10.71	−6.41	2.53	
INV	−0.13	0.07	0.02	0.11	−0.61	−0.07		0.31
[t]	−1.34	0.79	0.47	2.36	−7.76	−1.26		
		0.05	0.02	0.11	−0.62	−0.09	0.04	0.31
[t]		0.49	0.64	2.23	−8.74	−1.47	0.47	

Table S11 : The Penman-Zhang (2020a) Accounting-based Factors, with Operating Profits-to-price (Op/P)

Section 4.9 details operating profits-to-price (Op/P), return on equity (RoeA), and expensed investment-to-lagged price (ExpInv/P). Panel A shows the $4 \times 3 \times 3$ portfolios from sequential sorts on Op/P, RoeA, and ExpInv/P. At the end of June of each year t, we split stocks into 4 Op/P groups based on negative Op/P and NYSE breakpoints of positive Op/P. Within each Op/P portfolio, we split stocks into RoeA terciles with NYSE breakpoints. Within each Op/P-RoeA portfolio, we split stocks into ExpInv/P terciles with NYSE breakpoints. Monthly value-weighted returns are calculated from July of year t to June of $t+1$, and the portfolios are rebalanced in June-end of $t+1$. The SUM factor is the high Op/P-low RoeA-high ExpInv/P portfolio minus the low Op/P-high RoeA-low ExpInv/P portfolio. Columns denoted "Col. 3−7" show the results for the Low RoeA-High ExpInv/P portfolio minus the high RoeA-low ExpInv/P portfolio. In Panel B, the Penman-Zhang investment factor (INV) is the value-weighted high-minus-low tercile returns from annual one-way sorts on the NYSE breakpoints of INV/P (change in total assets scaled by lagged market equity). All t-values are adjusted for autocorrelations and heteroscedasticity.

Panel A: The Penman-Zhang $4 \times 3 \times 3$ benchmark portfolios on Op/P, annual Roe, and ExpInv/P

RoeA	Low	Low	Low	M	M	M	High	High	High	Col.
ExpInv/P	Low	M	High	Low	M	High	Low	M	High	3−7
	Average excess returns, $\overline{R}$									
Op/P<0	−0.43	0.47	0.97	0.21	0.52	0.80	0.53	0.50	0.75	0.43
Low Op/P	0.31	0.64	0.76	0.20	0.57	0.64	0.43	0.63	0.72	0.33
M	0.51	0.50	1.14	0.49	0.59	0.86	0.67	0.73	0.82	0.47
High Op/P	0.89	0.71	0.91	0.68	0.89	0.91	0.56	0.86	0.78	0.36
SUM										0.48
	The q-factor alpha, α_q ($p_{\mathrm{GRS}} = 0.00$)									
Op/P<0	−0.87	0.14	0.77	−0.35	0.07	0.33	−0.01	0.19	0.55	0.77
Low Op/P	−0.33	−0.02	0.21	−0.35	0.03	0.05	−0.04	0.11	0.18	0.25
M	−0.20	−0.30	0.32	−0.23	−0.24	−0.03	0.01	0.00	0.05	0.31
High Op/P	0.21	−0.02	0.14	0.02	0.23	0.06	−0.14	0.05	0.00	0.28
SUM										0.18
	The q^5 alpha, α_{q^5} ($p_{\mathrm{GRS}} = 0.04$)									
Op/P<0	−0.66	−0.13	0.72	−0.19	−0.08	0.06	0.33	0.19	0.32	0.40
Low Op/P	−0.05	0.02	0.10	−0.20	0.01	0.04	−0.04	0.11	0.19	0.14
M	−0.19	−0.25	0.26	−0.19	−0.24	0.02	−0.06	−0.05	−0.04	0.32
High Op/P	0.24	−0.09	0.11	0.12	0.26	0.10	0.00	0.06	0.01	0.11
SUM										0.15

RoeA	Low	Low	Low	M	M	M	High	High	High	Col.
ExpInv/P	Low	M	High	Low	M	High	Low	M	High	3−7
	$t_{\overline{R}}$									
Op/P<0	−0.94	1.09	2.10	0.48	1.26	2.06	1.37	1.31	1.77	1.04
Low Op/P	1.40	2.54	2.56	1.08	2.84	3.02	1.87	3.11	3.34	1.72
M	3.08	2.21	4.85	2.77	2.98	4.01	3.52	3.63	3.97	2.69
High Op/P	4.43	2.77	3.35	3.72	4.63	3.64	2.77	3.92	3.19	1.71
SUM										2.09
	t_q									
Op/P<0	−2.68	0.50	2.62	−1.19	0.24	1.50	−0.02	0.69	1.75	1.96
Low Op/P	−2.37	−0.14	1.44	−3.57	0.27	0.49	−0.40	1.17	1.81	1.41
M	−1.75	−2.34	2.81	−2.07	−2.35	−0.22	0.07	−0.02	0.39	1.90
High Op/P	1.27	−0.10	0.75	0.12	1.80	0.40	−0.96	0.36	−0.03	1.20
SUM										0.85
	t_{q^5}									
Op/P<0	−1.85	−0.43	2.32	−0.63	−0.26	0.24	0.96	0.65	0.97	0.88
Low Op/P	−0.38	0.13	0.65	−2.00	0.16	0.40	−0.38	1.12	1.66	0.73
M	−1.51	−1.76	2.32	−1.55	−2.13	0.16	−0.50	−0.40	−0.34	2.04
High Op/P	1.27	−0.57	0.61	0.74	1.81	0.68	−0.01	0.46	0.06	0.46
SUM										0.70

Panel B: Factor spanning tests between the Penman-Zhang 3-factor model and the q models

	$\overline{R}$	α	β_{Mkt}	β_{SUM}	β_{INV}	R^2
R_{Me}	0.27	0.10	0.15	0.23	0.22	0.26
[t]	2.22	0.97	6.06	9.77	3.90	
$R_{\mathrm{I/A}}$	0.33	0.29	−0.11	0.13	−0.36	0.45
[t]	4.10	4.58	−4.99	10.33	−7.27	
R_{Roe}	0.51	0.64	−0.11	−0.17	−0.10	0.18
[t]	4.96	7.33	−3.27	−7.47	−1.24	
R_{Eg}	0.80	0.92	−0.19	−0.05	−0.11	0.26
[t]	9.69	13.70	−8.90	−3.41	−1.97	

	$\overline{R}$	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}	R^2
SUM	0.48	0.18	0.01	0.63	1.12	−0.49		0.37
[t]	2.09	0.85	0.16	6.69	9.74	−5.11		
		0.15	0.01	0.63	1.11	−0.50	0.05	0.37
[t]		0.70	0.26	6.64	9.30	−4.57	0.36	
INV	−0.13	0.07	0.02	0.11	−0.61	−0.07		0.31
[t]	−1.34	0.79	0.47	2.36	−7.76	−1.26		
		0.05	0.02	0.11	−0.62	−0.09	0.04	0.31
[t]		0.49	0.64	2.23	−8.74	−1.47	0.47	