

Comparing portfolios built from intrinsic-value-based stock picks versus market-cap-weighted indices

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Abstract. *This study examines whether a portfolio selected on intrinsic value differs structurally from a capitalization-weighted portfolio drawn from the same universe. A random sample of 29 S&P 500 firms was valued with a free-cash-flow-to-the-firm discounted cash flow model; the 15 most undervalued names formed an equally weighted intrinsic-value portfolio, compared against a capitalization-weighted benchmark built from the same sample. The intrinsic-value portfolio showed lower valuation multiples, a higher dividend yield, a sector mix tilted toward cyclical and staple industries, and markedly lower representation among the largest firms. A three-month return comparison is reported for illustration only.*

Keywords: intrinsic value, discounted cash flow, market efficiency, capitalization weighting, portfolio construction.

JEL Classification: G11, G12, G14.

1. Introduction

The debate between active and passive investing remains one of the most persistent in finance. Passive strategies replicate a market index, typically weighted by capitalization, while active strategies attempt to identify mispriced securities. Evidence that most active managers fail to beat their benchmark once costs are included has strengthened the case for passive investing, yet value investors continue to argue that market prices do not always reflect a company's underlying economic worth.

This raises a narrower question: how much does a portfolio actually change when it is built from intrinsic-value estimates rather than market capitalization? Existing research approaches this mostly through returns, measuring whether value strategies, active management, or alternative weighting schemes beat their benchmarks over long samples, and remains caught in an unresolved debate over whether the patterns found reflect risk or mispricing. Less attention has gone to a simpler, structural question: holding the universe of available stocks fixed, how does an intrinsic-value selection rule reshape a portfolio compared with capitalization weighting, regardless of whether it wins on returns? This study addresses that question directly.

Intrinsic value is estimated for a random sample of 30 S&P 500 companies (reduced to 29 once a bank is excluded, since a free-cash-flow-to-the-firm model does not suit bank financials) using a discounted cash flow (DCF) approach, all valued at a single formation date. The 15 most undervalued firms are combined into an equally weighted intrinsic-value portfolio, and a capitalization-weighted benchmark is built from the same 29 names. Holding the universe constant isolates the effect of the selection and weighting rule itself, rather than differences in which stocks happen to be available.

Three hypotheses are tested: H1, that the intrinsic-value portfolio shows stronger value characteristics (lower valuation multiples and a higher dividend yield) than the benchmark; H2, that it differs in sector allocation; and H3, that it is less represented among the largest firms in the sample.

The contribution is descriptive rather than a claim about which approach performs better. A random sample reduces selection bias and allows differences between the portfolios to be attributed to the valuation and weighting method rather than to which stocks happen to be available. Because any difference in realized returns can always be attributed to the assumed model of risk rather than genuine mispricing, returns are reported only as illustration, not as evidence for or against outperformance. The remainder of the article reviews the relevant literature, sets out the valuation and comparison methodology, presents results across the three structural dimensions plus an illustrative return comparison, and concludes with the study's implications and limitations.

2. Literature Review

The starting point for this study is the efficient market hypothesis (EMH), most influentially stated by Fama (1970: pp. 383), who describes an efficient market as one in which prices fully reflect available information, sorted into weak, semi-strong, and strong forms

depending on which information set is assumed to be reflected. Fama found that the weak and semi-strong forms held up reasonably well, while the strong form did not, since insiders retain access to information prices do not yet reflect. This matters here because semi-strong efficiency is the central argument against what this study attempts: if public financial data is already priced in, an independent DCF valuation built from the same public data should not reliably find mispriced stocks. The intrinsic-value rule tested in this study assumes the opposite: that market price is not always the best estimate of value.

Efficiency, however, cannot be tested independently of a model of expected returns. For a researcher to judge whether prices incorporate all available information, they first need a model of what returns should look like in a normal, efficient market, and that is the model Fama (1970) builds his own analysis on. If a test then appears to show the market inefficient, the problem may just as easily lie with that assumed model of returns as with the market itself. This is the “joint hypothesis problem,” and it has direct consequences for this study: any difference in returns between the two portfolios built here could always be attributed to the chosen model of normal returns rather than to a genuine mispricing, which is a central reason the study is framed as a descriptive comparison rather than a test of efficiency. There are also theoretical and empirical reasons to doubt perfect efficiency. Grossman and Stiglitz (1980) argue that if prices already reflected all information, no one would be paid to gather it, so some inefficiency must persist to reward analysis, which is a promising starting point for a study built around independent valuation. Empirically, Fama and French (1992: pp. 427) show that firm size and the book-to-market ratio explain differences in average returns that market beta cannot, describing the relationship between beta and average return as essentially flat once size is taken into account, while Lakonishok, Shleifer and Vishny (1994: pp. 1541) argue such patterns instead reflect “the suboptimal behavior of the typical investor,” who systematically overpays for high-growth stocks and underpays for value stocks. The same evidence supports both readings. Fama and French treat it as a reward for risk that keeps the market efficient under a riskier model of returns, while Lakonishok, Shleifer and Vishny treat it as a mistake the efficient-market view cannot easily explain, and the debate remains unsettled, which is precisely why a comparison of price against independently estimated value remains relevant.

The study also sits within the active-versus-passive debate. Sharpe's (1991) “Arithmetic of Active Management” shows, by accounting logic rather than data, that because active and passive investors together make up the entire market, the average actively managed dollar must underperform the average passively managed dollar once costs are subtracted. This is an identity that holds in every period rather than a pattern that happens to appear in some samples and not others. Carhart (1997: pp. 57) supports this empirically, finding that apparent fund manager skill is largely explained by common return factors and cost differences rather than genuine stock-picking ability, so that persistence in fund performance rarely reflects anything more than exposure to the same systematic patterns. Sharpe also anticipates the obvious objection that some studies appear to show active managers beating the index, arguing that such results typically trace to measurement problems, such as “passive” benchmarks that are not truly passive, survivorship bias in the active sample, or an equal-weighted fund average that tilts toward small companies relative to the market, rather than to a flaw in the underlying logic. His arithmetic, however, applies

only to the average active investor; it does not, and cannot, rule out a specific selection rule beating the benchmark, which is the space this study's intrinsic-value approach occupies. The study does not attempt to overturn Sharpe's logic; it only asks whether a valuation-based selection rule produces a portfolio that differs systematically from the capitalization-weighted default his argument reinforces as the standard passive benchmark.

Where the EMH argues against active selection, the value-investing tradition, tracing to Graham and Dodd and described by Lakonishok, Shleifer and Vishny (1994: pp. 1541) as the founders of value investing, argues that a security's intrinsic value, derived from its fundamentals, can diverge from its market price, and that buying below intrinsic value is profitable. This idea gained empirical support when Fama and French (1992) identified the book-to-market ratio as a strong predictor of returns (the "value premium"), later formalized in their three-factor model (Fama and French, 1993). Interpretation of the value premium remains disputed: Fama and French read it as compensation for risk, while Lakonishok, Shleifer and Vishny (1994) read it as the correction of investors' predictable mistakes. This study, using a small descriptive sample, cannot settle that dispute; it can only show that the two portfolios differ, leaving the reason (risk, genuine mispricing, or the weighting rule itself) open.

Intrinsic value is estimated here using discounted cash flow (DCF) valuation, following the free-cash-flow-to-the-firm approach set out by Damodaran (2012), where expected free cash flows are discounted at the weighted average cost of capital (WACC) to an enterprise value and then converted to equity value per share. This is the most direct way of turning Graham and Dodd's qualitative notion of intrinsic value into a reproducible number. DCF carries weaknesses that matter for this study's design. Because cash flows are forecast explicitly for only a limited period, typically five to ten years, the terminal value typically dominates the total estimate (Damodaran, 2012), and because the constant-growth terminal-value formula divides by the gap between the discount rate and the assumed growth rate, that gap shrinking even slightly can move the whole valuation substantially, making the result highly sensitive to the assumed discount rate and long-run growth rate. Penman and Sougiannis (1998) find that DCF and dividend-discount models produce larger valuation errors than accrual-earnings models over the periods they test, attributing this to the terminal-value problem; Penman (2001: pp. 15) notes that free cash flow is a "perverse valuation attribute" because a firm investing to build value depresses its own near-term cash flow, so that a growing, value-creating company can show low or negative free cash flow for years, pushing an even larger share of its value into the fragile terminal estimate. Kaplan and Ruback (1995), by contrast, find DCF estimates come within roughly ten percent of observed transaction values on average when cash flows are forecast carefully against a real transaction price to anchor them, performing at least as well as valuations based on comparable companies. The literature's overall lesson is not that DCF should be rejected, since it remains the standard tool in practice and the one closest to the concept of intrinsic value, but that a single DCF figure should not be treated as exact. This motivates two design choices adopted below: every valuation is accompanied by a sensitivity analysis rather than reported as a fixed number, and realized performance is treated only as illustration, since the selection behind it is itself built on uncertain estimates.

The benchmark used for comparison is a capitalization-weighted index, in which each company's weight equals its share of total market value. This is the approach underlying the S&P 500 and most index funds, requiring little rebalancing since weights adjust automatically as prices move, and, under CAPM assumptions, the portfolio offering the best available mix of risk and return. Its popularity follows directly from that property, and it is also the passive default the average active manager cannot beat after costs, as Sharpe's arithmetic showed above. The most prominent critique comes from the fundamental-indexation literature: Arnott, Hsu and Moore (2005: pp. 83) argue that if prices contain errors, meaning they move away from fair value even temporarily, then weighting by market capitalization automatically puts more money into overvalued stocks and less into undervalued ones, so that capitalization weighting "assuredly overweights the overvalued stocks and underweights undervalued stocks." They propose weighting companies by fundamental measures of size instead, such as book value, earnings, dividends, sales, and employment, and report that indices built this way have historically outperformed their capitalization-weighted equivalents while holding the same stocks at different weights.

This claim needs to be treated with some care, for two reasons. First, it only holds if prices are wrong in a way an investor can actually use: under semi-strong efficiency, where price is an unbiased estimate of value and firm size alone says nothing about whether a stock is over- or undervalued, pricing errors are as likely to run one way as the other, and capitalization weighting carries no built-in penalty. Under that reading, fundamental indexation is not really a distinct passive strategy but an active value strategy presented as passive, which places it, like the intrinsic-value rule tested here, on the disputed side of the efficiency debate rather than settling it. Second, Arnott, Hsu and Moore are principals in a firm that sells fundamental-index products, and their outperformance figures come from a long historical back-test, so their commercial interest and the usual caveats around back-tested results are worth bearing in mind. The underlying idea nonetheless has a longer, less commercially entangled history: Haugen and Baker (1991) argued years earlier, without a comparable commercial stake, that capitalization-weighted portfolios are not the optimal risk-return tradeoff and that alternative weightings can do better. This study takes from the literature its core mechanism, that capitalization weighting concentrates capital in the largest names and, if prices are wrong, tilts toward the overvalued, without relying on the reported outperformance, which motivates two of its comparison dimensions: sector composition and representation among the largest firms.

Together, these strands form a single argument: the EMH provides the case against active selection; Sharpe's arithmetic sets the capitalization-weighted benchmark as the default the average manager cannot beat; the value-investing tradition provides the disputed counter-case that price and value can diverge systematically; DCF is the tool used to estimate that divergence while carrying its own fragility; and critiques of capitalization weighting suggest the passive default itself may be structurally biased toward large, overvalued names. Existing research addresses this question, whether independent valuation can differ from market price in a systematic and useful way, almost entirely through returns, using large samples, long histories, and performance measures, and remains caught in the unresolved risk-versus-mispricing debate. Less attention has gone to the simpler, structural question this study takes on: holding the universe of stocks fixed, how does an intrinsic-

value selection rule reshape a portfolio's valuation characteristics, sector composition, and representation among large firms, independent of whether it beats the market on returns? The contribution is therefore descriptive and exploratory: by fixing the universe through random sampling and prioritizing structural characteristics over performance, the study makes the mechanism by which intrinsic-value selection reshapes a portfolio visible and reproducible, without claiming to resolve the risk-versus-mispricing debate or to demonstrate a superior strategy.

3. Research Methodology

This study follows a mixed quantitative-descriptive design. It is quantitative in its underlying data, including cash-flow forecasts, discount rates, implied values, portfolio weights, valuation ratios, and returns, but descriptive in aim, measuring two portfolios built from a fixed universe and comparing them along four predetermined dimensions rather than testing statistical significance. With a single formation date and fewer than 30 firms, the sample is too small to support inferential testing of returns, and, following the joint hypothesis problem discussed above, testing efficiency directly is not the intention regardless. The design instead makes the selection mechanism itself visible: how an intrinsic-value rule and a capitalization-weighting rule, applied to the same stocks, produce structurally different portfolios.

The central research question is whether an intrinsic-value-based portfolio differs systematically from a capitalization-weighted benchmark drawn from the same fixed universe. Three hypotheses operationalize this: H1 predicts the intrinsic-value portfolio shows stronger value characteristics (lower P/E, P/B, and EV/EBITDA, higher dividend yield); H2 predicts a different sector allocation; H3 predicts lower representation among the sample's largest firms. A fourth, non-hypothesized comparison reports realized holding-period returns for illustration only.

The universe is the S&P 500. Thirty companies were drawn using Excel's random-number generator, each company having been numbered 1–500 in advance, removing any possibility of favourable stock-picking. One name, Citigroup, was excluded because the free-cash-flow-to-the-firm (FCFF) model does not suit banks, whose interest expense is part of operating activity rather than financing. This leaves 29 non-bank large-cap firms. (An insurance broker, Brown & Brown, was retained since its fee-based revenue fits the FCFF template.) All valuations use a single formation date of 27 February 2026; the two portfolios are then tracked over a three-month window from 2 March to 2 June 2026. All financial-statement, forecast, and market data, including market capitalization, shares outstanding, beta, the risk-free rate, and the equity risk premium, came from a single source, LSEG Workspace, to keep inputs consistent across firms.

Free cash flow to the firm was forecast explicitly for each company over a multi-year horizon, built up from consensus revenue-growth expectations, historical and projected operating margins, and normalized tax rates, adjusted for capital expenditure and working-capital needs; the weighted average cost of capital (WACC) used to discount those flows was built firm-by-firm from each company's beta, a common equity risk premium, and the

prevailing risk-free rate. A terminal value covering cash flows beyond the explicit horizon was then added, using the constant-growth (Gordon growth) formula:

$$TV = [FCF_n \times (1 + g)] \div (WACC - g)$$

The perpetual growth rate g is set case-by-case for each firm, ranging across the sample from roughly 1% (e.g. Kraft Heinz, reflecting its weak recent record as a mature consumer-staples business) to roughly 2.7% (e.g. Amazon, reflecting its scale and continued expansion), always kept below long-run nominal GDP growth of approximately 4% so that the valuation does not explode as g approaches WACC. Discounting the explicit cash flows and the terminal value back to the present and summing gives enterprise value:

$$\text{Enterprise Value} = \sum_n [FCF_t \div (1+WACC)^t] + [TV_n \div (1+WACC)^n]$$

Equity value follows by adding cash, short-term investments, and long-term investments, and subtracting short- and long-term debt:

$$\text{Equity Value} = EV + \text{Cash \& STI} + LTI - LT Debt - ST Debt$$

Dividing equity value by shares outstanding gives the implied share price, and comparing it with the market price on the formation date gives the upside/downside used to rank and select stocks:

$$\text{Upside/Downside} = (\text{DCF Implied Share Price} \div \text{Market Share Price}) - 1$$

Because a single DCF figure is fragile, as the literature review discussed, every valuation was stress-tested with a sensitivity grid varying WACC and the perpetual growth rate by ± 1.0 percentage point in 0.5-point steps around each firm's own estimate, and portfolio membership was checked at the extremes of that grid (Section 4.2).

Two portfolios were then built from the same 29 names, using deliberately opposite construction rules so that any structural difference between them can be traced to the rule itself rather than to the underlying stocks. The intrinsic-value portfolio holds the 15 most undervalued firms, the top 50% by upside, a cutoff fixed in advance rather than tied to a particular outcome, each equally weighted at $1/15$ ($\approx 6.67\%$). Equal weighting was chosen over weighting by the size of the upside because the upside figure itself is sensitive to model assumptions, and ranking a portfolio by a fragile number would concentrate the biggest bets in the valuations the study is least confident in. The capitalization-weighted benchmark applies the opposite logic to the same 29 names: it holds every firm regardless of valuation, weighted by market capitalization at the formation date, replicating standard index construction. Because it is drawn from only 29 names rather than a broad index, it can concentrate weight in a few large companies to a degree unlikely across the full S&P 500. This is a small-sample effect discussed among the limitations below and revisited when Amazon's weight is examined in Section 4.4. The S&P 500 itself is shown alongside as background context only, since its roughly 500-stock universe is not comparable in scale to the 29-stock sample, so any gap against it reflects universe size as much as selection method.

The two portfolios are compared across four dimensions: valuation characteristics (P/E, P/B, EV/EBITDA, dividend yield, reported as both median and weighted average), sector

composition (GICS classification, expressed as percentage of portfolio weight), representation among large-cap firms (the count of intrinsic-value holdings falling in the top half of the sample by market capitalization), and performance (three-month holding-period return, reported only as illustration given the short window and small sample).

The study carries several limitations that bound its conclusions. The sample of 29 firms from a single random draw and single formation date cannot be generalized to the broader market, and the sampling universe (current S&P 500 membership) introduces a degree of survivorship bias, though this matters little over a three-month window. Consensus forecasts and market parameters were collected on 14 May 2026, roughly ten weeks after the observation window began, which introduces look-ahead bias that affects the illustrative return comparison but not the structural valuation, sector, and representation findings, which rely on data available at formation. DCF valuations further depend on subjective forecasting assumptions and are more reliable for mature, stable-cash-flow firms than for cyclical or high-growth names; a large gap between market price and DCF estimate should not automatically be read as mispricing, since the model may not capture every risk. Reported returns are gross, unbalanced, and cover only three months, too short, and too easily dominated by single-stock noise, to support any claim about long-run investment performance.

4. Results and Analysis

This section applies the methodology above to the random sample. Section 4.1 presents the DCF valuation output and the resulting ranking; Section 4.2 checks the ranking's stability under a sensitivity analysis; Sections 4.3–4.5 compare the portfolios along the three hypothesized structural dimensions; Section 4.6 reports realized returns as illustration; Section 4.7 relates the findings to the literature.

4.1. Valuation results and the under/overvaluation ranking

Each of the 29 companies was valued with the FCFF DCF model described above; the implied price was compared with the closing price on the formation date (27 February 2026) to give an upside/downside figure, and the 15 names with the largest upside form the intrinsic-value portfolio. Table 1 reports the full ranking.

Table 1. *DCF valuation results and the under/overvaluation ranking*

Rank	Ticker	Company	GICS sector	Implied price	Price 27 Feb	Upside	Sel.
1	AMCR.N	Amcor PLC	Materials	\$145.54	\$48.43	200.5%	✓
2	KHC.OQ	Kraft Heinz Co	Consumer Staples	\$59.44	\$24.61	141.5%	✓
3	EXPE.OQ	Expedia Group Inc	Consumer Discretionary	\$449.18	\$215.69	108.3%	✓
4	VLO.N	Valero Energy Corp	Energy	\$394.82	\$204.64	92.9%	✓
5	KMB.OQ	Kimberly-Clark Corp	Consumer Staples	\$209.87	\$111.44	88.3%	✓
6	HAL.N	Halliburton Co	Energy	\$66.28	\$36.00	84.1%	✓
7	GEHC.OQ	GE Healthcare Technologies	Health Care	\$149.36	\$84.27	77.2%	✓
8	DAL.N	Delta Air Lines Inc	Industrials	\$110.67	\$65.70	68.4%	✓
9	BRO.N	Brown & Brown Inc	Financials	\$112.47	\$71.82	56.6%	✓

Rank	Ticker	Company	GICS sector	Implied price	Price 27 Feb	Upside	Sel.
10	EBAY.OQ	eBay Inc	Consumer Discretionary	\$122.10	\$90.86	34.4%	✓
11	OTIS.N	Otis Worldwide Corp	Industrials	\$120.84	\$92.56	30.6%	✓
12	MAS.N	Masco Corp	Industrials	\$92.21	\$71.62	28.8%	✓
13	JBL.N	Jabil Inc	Information Technology	\$307.49	\$264.99	16.0%	✓
14	PG.N	Procter & Gamble Co	Consumer Staples	\$192.05	\$167.20	14.9%	✓
15	DD.N	Dupont De Nemours Inc	Materials	\$55.73	\$50.04	11.4%	✓
16	KMI.N	Kinder Morgan Inc	Energy	\$36.90	\$33.27	10.9%	
17	WM.N	Waste Management Inc	Industrials	\$262.30	\$240.84	8.9%	
18	CARR.N	Carrier Global Corp	Industrials	\$70.06	\$64.40	8.8%	
19	ORCL.N	Oracle Corp	Information Technology	\$155.11	\$145.40	6.7%	
20	DOV.N	Dover Corp	Industrials	\$225.93	\$225.50	0.2%	
21	ALB.N	Albemarle Corp	Materials	\$178.55	\$178.67	-0.1%	
22	UNP.N	Union Pacific Corp	Industrials	\$234.26	\$264.98	-11.6%	
23	AKAM.OQ	Akamai Technologies Inc	Information Technology	\$84.12	\$98.39	-14.5%	
24	GRMN.N	Garmin Ltd	Consumer Discretionary	\$211.60	\$252.83	-16.3%	
25	VEEV.N	Veeva Systems Inc	Health Care	\$118.51	\$182.01	-34.9%	
26	AMZN.OQ	Amazon.com Inc	Consumer Discretionary	\$95.62	\$210.00	-54.5%	
27	PWR.N	Quanta Services Inc	Industrials	\$249.27	\$563.08	-55.7%	
28	ISRG.OQ	Intuitive Surgical Inc	Health Care	\$177.20	\$503.51	-64.8%	
29	COST.OQ	Costco Wholesale Corp	Consumer Staples	\$319.90	\$1010.79	-68.4%	
--	C.N	Citigroup Inc	Financials	n/a	n/a	n/a	

Note: calculations based on data from LSEG Workspace.

The spread of mispricing is wide. Amcor screens as the most undervalued name, with an implied price more than triple its market price, and Kraft Heinz, Expedia, Valero, Kimberly-Clark, and Halliburton all show upside above eighty percent; Costco, Intuitive Surgical, Quanta Services, and Amazon look heavily overvalued at the other end, trading well above the value the model implies. The undervalued half is dominated by cyclical and mature businesses: energy (Valero, Halliburton), materials (Amcor, Dupont), consumer staples (Kraft Heinz, Kimberly-Clark, Procter & Gamble), and a handful of industrials. The overvalued half holds large growth and quality names such as Amazon, Costco, Intuitive Surgical, and Veeva. The three technology names in the sample split across the cut, with Jabil inside it and Oracle and Akamai outside, so the pattern is closer to a price-versus-value rule that happens to capture many cyclical and staple companies than to a strict sector rule; this connection between the valuation screen and the cash-flow profile of these businesses resurfaces in Sections 4.3 and 4.7. The gap between selection and exclusion is small for a few borderline names. Dupont, the last stock included, shows an 11.4% upside against Kinder Morgan's 10.9% as the first excluded, which is exactly why the sensitivity check below matters: if the ranking flipped easily near that boundary, the selection would be an artifact of the model's assumptions rather than a real signal in the data.

4.2. Sensitivity analysis results

Each valuation was recomputed across a grid varying the terminal growth rate and discount rate (an adverse case lowering growth and raising the discount rate by 0.5pp each; a favourable case doing the reverse), and portfolio membership was re-checked at both extremes.

Table 2. *Portfolio membership under the sensitivity scenarios*

Scenario	Names held	Dropped out	Newly entering
Base case (as reported)	15 of 15	--	--
Adverse (g -0.5pp, WACC +0.5pp)	14 of 15	PG	DOV
Favourable (g +0.5pp, WACC -0.5pp)	13 of 15	DD, JBL	KMI, WM

Note: calculations based on data from LSEG Workspace.

The portfolio holds up well: only one name changes in the adverse case and two in the favourable case, both times among the borderline firms identified above. The deeply undervalued names (Amcor, Kraft Heinz) and the heavily overvalued names (Amazon, Costco) stay on their respective sides in every scenario. The selection sorts the sample into a clearly cheap group and a clearly expensive group, with only two or three borderline names able to swap places, which is sufficient stability for the structural comparison that follows.

4.3. Dimension 1: Valuation characteristics (H1)

Four characteristics were collected for every holding: P/E, P/B, EV/EBITDA, and dividend yield, each reported as both a median (robust to a single extreme name) and a weighted average. For the three multiples, a weighted harmonic mean was used to keep large outlier values from dominating the result; dividend yield, which sums cleanly across holdings, uses an ordinary weighted average.

Table 3. *Valuation characteristics of the two portfolios*

Characteristic	Bench. median	Bench. wtd. avg	IV median	IV wtd. avg	H1 met?
P/E	23.3	29.1	18.6	18.9	Yes (lower)
P/B	4.4	5.6	2.9	2.5	Yes (lower)
EV/EBITDA	14.9	18.1	11.9	10.8	Yes (lower)
Dividend yield	1.3%	0.7%*	2.0%	2.3%	Yes (higher)

Note: *weighted-average dividend yield counts non-payers as zero; Amazon alone is 52% of the benchmark and pays no dividend. Calculations based on data from LSEG Workspace.

The intrinsic-value portfolio is cheaper on all three multiples and offers a higher dividend yield, on both the median and the weighted-average basis, so H1 is supported on every measure, and the differences are not small: on the weighted figures the benchmark's EV/EBITDA is about seventy percent higher than the value portfolio's, and its price-to-book is more than double. The benchmark's weighted dividend yield of 0.7% reflects Amazon's 52% weight and zero payout; counting only its dividend-paying constituents lifts that figure to about 1.6%, but since payers are less than half the benchmark by weight, the lower, all-constituent figure is the honest one. Even against that adjusted figure, the intrinsic-value portfolio's yield remains higher, and most of its holdings pay a dividend. Kraft Heinz, which sits in the intrinsic-value portfolio with a normalized P/E above 100 due to depressed normalized earnings rather than a high price, is a useful robustness check:

on every other measure it is among the cheapest names in the sample, with one of the lowest P/B ratios and one of the highest dividend yields, and removing it from both portfolios shifts the intrinsic-value portfolio's harmonic P/E from 18.9 to 17.9 and its EV/EBITDA from 10.8 to 11.0, with no change of direction in any result and almost no movement in the benchmark, since Kraft Heinz is only about half a percent of its composition. The conclusion, in other words, does not depend on a single name. Cheaper multiples are consistent with genuine undervaluation, but equally consistent with the value premium being a reward for risk, and a sample this small cannot distinguish the two readings; the finding supported here is the descriptive one, that intrinsic-value selection with equal weighting produces a portfolio whose valuation characteristics differ from the benchmark in the predicted direction, for reasons discussed further in Section 4.7.

4.4. Dimension 2: Sector composition (H2)

Each holding was classified by GICS sector and weights summed within sector, using market-cap weights for the benchmark and equal weights for the intrinsic-value portfolio.

Table 4. *Sector composition of the two portfolios*

GICS sector	Benchmark	Intrinsic value	Difference (IV – bench.)
Consumer Discretionary	54.6%	13.3%	-41.3 pp
Consumer Staples	15.7%	20.0%	+4.3 pp
Energy	3.4%	13.3%	+9.9 pp
Financials	0.4%	6.7%	+6.3 pp
Health Care	3.7%	6.7%	+2.9 pp
Industrials	9.8%	20.0%	+10.2 pp
Information Technology	11.3%	6.7%	-4.6 pp
Materials	1.1%	13.3%	+12.3 pp

Note: calculations based on data from LSEG Workspace.

The two sector profiles differ sharply, supporting H2, though part of the contrast is mechanical: because the intrinsic-value portfolio is equally weighted, each sector's weight is simply its number of holdings multiplied by one-fifteenth, so Consumer Staples and Industrials each reach twenty percent purely because they hold three names apiece. The benchmark concentrates by construction and equal weighting flattens by construction, so some of the gap in Table 4 reflects that mechanical fact rather than the selection rule itself. A large share of the apparent Consumer Discretionary tilt compounds this with a single-stock effect: Amazon alone is 52% of the benchmark, and the sector's 54.6% weight is, read literally, less a sector bet than a bet on one company; removing Amazon collapses the benchmark's Consumer Discretionary weight below five percent, and Consumer Staples (Costco, Procter & Gamble) becomes its largest sector instead. Even so, a genuine tilt survives once Amazon is set aside: the intrinsic-value portfolio remains overweight the cyclical, asset-heavy, lower-multiple sectors (Energy, Materials, and Industrials) and underweight Information Technology, an underweight that widens further once Amazon is removed, since Oracle then makes up a large share of the benchmark's remaining technology weight and the intrinsic-value screen never selected it. This is coherent with Section 4.3: the portfolio is cheaper because it leans toward cyclical sectors the market holds lightly and away from the expensive growth names dominating the benchmark. A sector-level Herfindahl index of 0.35 for the benchmark against 0.15 for the intrinsic-value portfolio (falling to 0.22 for the benchmark without Amazon) puts the concentration into

one number: the benchmark is more than twice as concentrated at the sector level despite both portfolios holding the same eight sectors, and much of that concentration traces to a single holding, a result that connects directly to the fundamental-indexation critique discussed in Section 2 and carries into the representation dimension below.

4.5. Dimension 3: Representation among large-cap firms (H3)

The 29 stocks were ranked by market capitalization and the 15 intrinsic-value holdings located within that ranking; the headline measure is how many fall in the top half by size.

Table 5. Representation among large-capitalization firms

Representation measure	Names not selected	Intrinsic-value portfolio
Holdings in top half by market cap (top 15)	10 of 14	5 of 15
Holdings in bottom half (rank 16–29)	4 of 14	10 of 15
Three largest firms captured (AMZN, ORCL, COST)	3 of 3	0 of 3
Share of total sample market value	85.6%	14.4%
Median market capitalization	\$81.5 bn	\$27.6 bn

Note: calculations based on data from LSEG Workspace.

The result is clear and H3 is supported. Only five of the fifteen intrinsic-value holdings sit in the sample's larger half by market capitalization, and none of the three largest firms (Amazon, Oracle, Costco) are represented at all. Since the intrinsic-value portfolio is drawn from the same universe as the benchmark, every one of its names appears in the benchmark by construction, so the two portfolios necessarily overlap, and the real question is where in the size distribution that overlap sits. By weight the answer is stark. Although every intrinsic-value holding is also present in the benchmark, those names account for only 14.4% of the benchmark's market value, while the 14 firms the screen does not select account for 85.6%, with Amazon, Oracle, and Costco alone making up roughly 71%; the overlap between the two portfolios sits almost entirely in the benchmark's most lightly weighted tail. The median intrinsic-value holding is a \$27.6bn company against \$81.5bn for the names not selected, and this gap needs little interpretation: the screen captures none of the three largest firms and overlaps with only 14.4% of the benchmark by weight. The screen and the index draw from opposite ends of the same size distribution, which is the clearest evidence in the study that intrinsic-value selection does not reproduce capitalization weighting, and in this sample does close to the opposite.

4.6. Dimension 4: Performance (illustrative)

The final comparison reports holding-period returns over the observation window (2 March – 2 June 2026), with the S&P 500 as reference. Because the window is roughly twelve weeks and the intrinsic-value portfolio holds only fifteen stocks, results are dominated by noise; this section is reported for completeness, not as evidence for or against either construction method.

Table 6. Holding-period returns over the observation window

Portfolio	Weighting	Return (2 Mar – 2 Jun 2026)
Cap-weighted benchmark (29 names)	Market cap	+17.6%
S&P 500 (price index, reference)	Market cap	+10.5%
Intrinsic-value portfolio (15 names)	Equal	–0.5%
Memo: equal-weighted full universe (29)	Equal	+4.0%

Note: price returns, dividends not reinvested. Calculations based on data from LSEG Workspace.

The benchmark won comfortably, but the reason ties back to Sections 4.4 and 4.5 rather than to a general case for capitalization weighting: Amazon rose about 22% over the window and, at 52% of the portfolio, drove roughly two-thirds of the benchmark's entire gain on its own, with Oracle (+68%) accounting for much of the rest. The benchmark did well because this particular window happened to be a good one for the handful of large names that dominate it, the same concentration that widened the structural gaps in Sections 4.3 to 4.5, only this time it helped rather than hurt. The intrinsic-value portfolio's near-flat result is the mirror image, precisely because equal weighting means no single holding can carry the whole portfolio's return: its best names (Jabil +41%, Valero +26%) were offset by its worst (GE Healthcare -26%, Otis -24%), netting out close to zero, while an equally weighted portfolio of all 29 names in the sample returned about 4% over the same window, suggesting that the specific selection, and not simply the choice to equal-weight, held the intrinsic-value portfolio back here. Flipping to a window where Amazon fell would, on this logic, likely invert the ranking entirely. The S&P 500 is included only as background: it holds roughly 500 stocks against 29 in either portfolio here, so part of any gap against it reflects the difference in universe size rather than the selection rule, and says little about whether either method adds value. Over this one short period the benchmark outperformed, driven almost entirely by concentration in a single stock, and the study draws no conclusion from it about which construction method is superior, which is exactly why performance is framed throughout as illustration only.

4.7. Discussion: relating the findings to the literature

Together, the four dimensions tell one story: the intrinsic-value portfolio is cheaper on independent multiples, tilted toward cyclical and staple sectors and away from technology, and under-represented among the largest firms. These findings appear to share a common mechanism. The heaviest capitalization weights in this universe sit in a handful of large, highly priced growth names, above all Amazon, and the DCF screen avoids them, which mechanically produces a cheaper, differently weighted, smaller-cap portfolio. The performance result in Section 4.6 is the same mechanism viewed from another angle: the very concentration that widens the structural gaps happened, in this particular window, to favour the benchmark.

Set against the EMH (Section 2), the findings sit on the disputed side without settling it. Under semi-strong efficiency, an independent valuation built from public data should mostly agree with market prices, yet the intrinsic-value portfolio differs systematically and predictably from the benchmark drawn from the same stocks. This is consistent with Grossman and Stiglitz's (1980) argument that some inefficiency must persist to reward analysis, and with Graham and Dodd's premise that price and value can drift apart. But the joint hypothesis problem means the finding cannot on its own prove inefficiency, since any gap can be attributed to the assumed model of returns instead; the lower multiples documented are equally consistent with Fama and French's reading of the value premium as compensation for risk and with Lakonishok, Shleifer and Vishny's reading of it as the correction of investor mistakes, and a sample of 29 stocks over three months cannot distinguish between them.

The evidence speaks most clearly to the structure of the capitalization-weighted portfolio itself, connecting to Sharpe's arithmetic and to the fundamental-indexation critique. Sharpe's point, that the average active dollar must fall behind the average passive default, is not in question here; the study instead shows that a valuation rule builds a portfolio that differs meaningfully from that passive default. The benchmark's defining feature turned out to be concentration: one stock at roughly 52% of the portfolio and the three largest names above 70% of its value, the same structural tilt Arnott, Hsu and Moore describe when they argue capitalization weighting channels money toward the largest names and, if prices contain errors, toward the overvalued ones. The study adopts their central mechanism while remaining neutral on their performance claim, consistent with the decision to treat returns as illustration only.

The contribution is meant to be illustrative and exploratory rather than a generalizable discovery about markets. By fixing the universe through random sampling and prioritizing valuation characteristics, sector composition, and representation among large-cap firms ahead of performance, the study makes the effect of choosing intrinsic value over capitalization weighting visible on a scale that is easy to follow from start to finish, with the sensitivity analysis in Section 4.2 giving confidence that the effect reflects the selection rule itself rather than one fragile set of assumptions. It should be just as clear what the study cannot claim: it cannot settle the risk-versus-mispricing debate, cannot prove that value selection earns higher returns, and cannot generalize from 29 stocks drawn once from the S&P 500 to the entire market. Within those limits, the study can say that an intrinsic-value approach and capitalization weighting, applied to the same companies, produce structurally different portfolios in their valuation profile, sector exposure, and concentration among the largest firms, and that the difference traces consistently, across all three dimensions, to how each method treats the largest and most expensive names in the sample.

5. Conclusion

This study examined how a portfolio constructed from intrinsic-value estimates differs from a capitalization-weighted portfolio drawn from the same universe of stocks, focusing on structural differences rather than on resolving the long-standing debate over whether active management can consistently beat passive investing. A random sample of S&P 500 companies was valued with a free-cash-flow-to-the-firm DCF model; the fifteen companies with the largest discount between estimated intrinsic value and market price formed the intrinsic-value portfolio, compared against a capitalization-weighted benchmark from the same sample, so that any difference between the portfolios could be attributed to the selection and weighting rule rather than to differences in available stocks.

The results show the two approaches produce meaningfully different portfolios. The intrinsic-value portfolio displayed stronger value characteristics, lower valuation multiples and a higher dividend yield, supporting H1. It showed a markedly different sector composition, tilted toward Energy, Consumer Staples, and Industrials rather than the technology- and mega-cap-heavy benchmark, supporting H2. And it showed substantially lower representation among the sample's largest firms, with none of the three largest

companies selected and only 14.4% of the benchmark's market value overlapping with the intrinsic-value names, supporting H3.

Together these findings indicate that intrinsic-value selection and capitalization weighting are not simply alternative routes to the same portfolio: even applied to identical companies, the two approaches produce different valuation profiles, sector exposures, and concentration among large firms, driven by the construction rules rather than by the investment universe itself.

This study does not claim that one approach is superior. The short observation period, limited sample size, and inherent uncertainty of DCF valuation prevent broad conclusions about long-term performance, and the debates over market efficiency, value investing, and active management reviewed in Section 2 remain unresolved. The lower multiples and different sector tilt documented here are as consistent with a genuine value signal as with a reward for risk, and a sample of this size cannot arbitrate between the two. The contribution is meant to be descriptive and exploratory: by isolating the effects of selection and weighting methodology within a fixed universe, the study makes visible the structural consequences of choosing intrinsic value over market capitalization in portfolio construction, a necessary step before any claim about which approach delivers better long-term outcomes. Future work could extend the comparison across multiple random draws and formation dates to test whether the structural gap documented here (in valuation, sector mix, and representation among the largest firms) is a stable feature of intrinsic-value selection or an artifact of this particular sample, and could examine longer holding periods once look-ahead bias in the forecast inputs can be more fully controlled.

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