A Cross-Framework Consensus Scoring System for US-Listed Equities: Methodology and Five-Year Backtest

Zaid Ghazal, Independent Researcher (Kiel, Germany)
invest-like (https://invest-like.com), an independent research platform.

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Abstract

This paper documents a deterministic, multi-framework scoring system that grades every US-listed operating equity against seven canonical investor philosophies: Warren Buffett, Benjamin Graham, Philip Fisher, Peter Lynch, Joel Greenblatt, Charles Munger, and Terry Smith. Each framework is implemented as a transparent pillar-weighted rubric that maps a stock's current fundamentals onto a 0 to 100 score, with hard cap deal-breakers applied where an investor's writing identifies explicit disqualifiers (for example heavy share dilution under Buffett, leverage above 1x EBITDA under Munger). Scores are translated into a five-level grade ladder (A+, A, B, C, D, F). Beyond the seven individual scores, we define a cross-framework consensus signal as the count of frameworks scoring a given stock at B+ or better (numerically, score greater than or equal to 60). We then evaluate the historical price performance of cohorts defined by their current consensus tier over a five-year lookback window, with results compared to the SPDR S&P 500 ETF (SPY) over the same window. In the canonical cohort of stocks where all seven frameworks currently grade the company at B+ or better (n equals 47, drawn from a universe of approximately 3,085 stocks passing the size and instrument-type filter), we observe a median five-year price return that exceeds SPY's five-year return by 73.8 percentage points, with 85 percent of the cohort posting positive five-year returns. We disclose the methodological limitations including survivorship bias and look-ahead bias, present per-framework standalone cohort results for comparison, and discuss why an ensemble of philosophically distinct lenses might select for business quality more robustly than any single lens. The methodology and scoring engine are fully documented in public source code; a public verdict API and per-ticker pages allow third parties to audit and reproduce any individual stock's score. This is a research artifact, not investment advice.

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1. Introduction

Retail and self-directed institutional investors face an oversupplied market of stock-screening tools. Most are pinned to a single philosophical commitment: a Graham screener applies one set of valuation and balance-sheet thresholds, a Greenblatt Magic Formula screener applies another, a "quality compounder" screener built around the Fundsmith style applies a third. A user who builds conviction from any one of these screens by construction inherits that framework's blind spots.

This is not a defect of the individual frameworks. Each canonical value-investing lens (Graham, 1934; Graham, 1949; Buffett's Berkshire Hathaway shareholder letters from 1965 onward; Fisher, 1958; Lynch, 1989; Greenblatt, 2005; Munger across various speeches and shareholder meetings; Smith, Fundsmith Annual Letters, 2010 onward) was articulated explicitly as a lens, not as a complete theory of equity selection. Graham's defensive investor framework deliberately excludes growth premiums and asset-light businesses where book value understates intrinsic value. Smith's quality-compounder framework deliberately excludes the entire deep-value universe Graham is searching in. Lynch's GARP framework deliberately excludes hyper-growth situations where next year's earnings can collapse, and equally excludes zero-growth businesses with no internal catalyst.

The contribution of this paper is not a new investment philosophy. It is the systematic implementation of seven existing philosophies as transparent, reproducible scoring rubrics, and the empirical investigation of what their cross-framework agreement selects for. A stock that scores well on Buffett's lens is a quality compounder bought at a fair price. A stock that scores well on Graham's lens is statistically cheap with a defensible balance sheet. A stock that scores well on Lynch's lens is growing into its multiple. These are different bets, and the philosophical literature makes no claim that they should overlap.

A stock that scores well on six or seven of these lenses, however, is qualitatively different. It is a name where the strongest published value-investing frameworks converge despite having different criteria and different blind spots. We hypothesize, and test below, that this convergence is rare, difficult to fake by tilting any single ratio, and produces a cohort whose forward-realized returns dominate any single-framework cohort across our test window.

Three notes on scope. First, the seven frameworks we implement are not exhaustive of the value-investing tradition. We exclude Walter Schloss (insufficient written rubric for systematic implementation), Howard Marks (philosophy is cycle-aware in a way that is hard to encode statically), and various contemporary practitioners whose published rules are downstream of those we already include. Second, the scoring is deterministic and rule-based; we do not apply machine learning, factor-model regressions, or any form of optimization over the historical price data. Third, this paper documents the methodology and a current-grade lookback backtest. A true point-in-time backtest with quarterly fundamental snapshots is in development; we identify this and other limitations explicitly in Section 5.

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2. Methodology

2.1 The pillar-weighted scoring primitive

Every framework in our system is implemented as a weighted average over a small number of pillars, each pillar in turn a weighted average over a small number of underlying signals. Each signal is mapped onto a 0 to 100 score by a piecewise-linear ramp:

```
ramp(value, lo, hi)  = 100 * clamp((value - lo) / (hi - lo), 0, 1)
ramp(value, lo, hi, invert=true)  = 100 - ramp(value, lo, hi)
```

The `invert` flag is used for ratios where lower is better (e.g. P/E, Net Debt / EBITDA). Null inputs are dropped from the weighted average rather than substituted with a neutral value, which avoids penalizing companies with missing data on optional pillars.

The output of a pillar's weighted average is itself an input to the framework's overall weighted average. Each framework therefore exposes a strictly auditable rubric: anyone with the same fundamental input vector can compute the same score.

2.2 The seven frameworks

We describe each framework's pillars and intentional exclusions. The exact ramp endpoints and weights are in the open-source code at `src/lib/scoring/`.

Buffett. Five pillars: economic moat (gross margin, operating margin, return on invested capital), durability of demand (five-year earnings stability, EPS maximum decline, revenue and EPS CAGR), owner-friendly management (share count CAGR, debt-to-equity, FCF-to-net-income, market-cap-increase-vs-retained-earnings), valuation (P/E, owner-earnings yield, EV/EBIT, earnings yield), and financial health (interest coverage, net debt to EBITDA, current ratio, FCF conversion). The overall Buffett-Fit Score weights moat and financial health at 25 percent each, valuation at 20 percent, and durability and management at 15 percent each.

Graham. Defensive value with a quantitative margin of safety. Pillars: earnings stability (10 consecutive years of positive earnings), conservative balance sheet (current ratio above 2, long-term debt below net working capital), dividend record (uninterrupted dividends for 20 plus years where applicable), modest valuation (three-year-average P/E below 15, P/B below 1.5, combined P/E times P/B below 22.5, the Graham number). The framework deliberately excludes growth premiums, technology without a multi-decade earnings record, and asset-light businesses where book value understates intrinsic value.

Fisher. Scuttlebutt-driven growth quality. Pillars: growth runway (revenue compounding because the underlying market is expanding, not share-take in a flat market), above-average R&D and salesforce productivity, management depth, profit margins improving with scale. The framework excludes asset-heavy and commodity businesses where reinvested R&D cannot compound, since Fisher's fifteen-point checklist is calibrated for businesses whose value comes from accumulated process knowledge.

Lynch. Growth at a reasonable price (GARP). Pillars: PEG ratio below 1, earnings growth in the 15 to 25 percent per year sweet spot, comprehensible business, insider buying combined with low institutional ownership. The framework excludes hyper-growth above 50 percent per year (fragility risk) and zero-growth businesses with no internal catalyst.

Greenblatt. The Magic Formula: rank the universe on capital efficiency (return on invested capital) and cheapness (earnings yield, EBIT over enterprise value), buy the top decile by combined rank. Pillars: high ROIC, high earnings yield, combined rank in the top 30 to 50 names. The framework excludes banks, insurance companies, utilities, and REITs (capital structures are not comparable to operating businesses) and intentionally ignores moat and management quality (it is a rules-based screen, not a qualitative read).

Munger. Quality plus simple business plus almost no debt. The strictest of the seven. Pillars: very high quality (ROE above 20 percent, ROIC above 15 percent, stable margins through cycles, no accounting irregularities), almost no debt (Munger's stated preference for zero leverage; net debt above 1x EBITDA fails this lens), simple business model, multi-decade demand stability. The framework excludes biotech binaries, financial engineering, heavy regulatory exposure, and leveraged compounders.

T. Smith. Quality compounders that turn cash into more cash year after year. Pillars: free cash flow conversion above 90 percent, return on capital employed above 25 percent consistently, pricing power (revenue growth ahead of inflation without volume tricks), capital-light economics. The framework excludes cyclicals, low-FCF-conversion businesses, and any business that requires balance-sheet leverage to hit its ROE target. Smith's framework explicitly excludes the deep-value universe Graham searches in.

2.3 Deal-breaker caps

The pillar-weighted average is elegant for monotonic preferences but fails on hard red flags. A stock can score 78 on the Buffett weighted average while quietly failing a non-negotiable like "ROIC actually positive on the most recent TTM" because fourteen other pillar inputs averaged out. Each canonical investor articulated such non-negotiables explicitly. Buffett: "I've seen more people fail because of liquor and leverage." Munger: "almost no debt." Smith: ROCE above 20 percent is non-negotiable.

We therefore apply per-framework deal-breaker caps after the pillar weighted average. The score and the pillar breakdown remain transparent; the letter grade is capped at a documented ceiling when a deal-breaker fires, with a human-readable `capReason` explaining which red flag triggered the cap.

Example caps (Buffett framework): - ROIC below 8 percent on both TTM and five-year average: grade capped at D. - ROIC negative on the most recent TTM: grade capped at D. - Share count growing above 3 percent per year over five years: grade capped at C, reason "heavy dilution dilutes future per-share value."

Analogous caps are defined for each of the other six frameworks. The complete list of caps is in `src/lib/scoring/deal-breakers.ts` in the open-source codebase.

2.4 Grade ladder

Each framework's 0 to 100 score maps to a letter grade as follows. Thresholds are the single source of truth used across the platform.

- A+: score in [85, 100]. Textbook fit; all pillars passed convincingly.
- A: score in [70, 85). Strong fit; multiple pillars pass, valuation either fair or only mildly stretched.
- B: score in [55, 70). Partial fit; the business is interesting, typically one pillar (often valuation or management) holds it back. We define a B+ tag at the lower boundary, score greater than or equal to 60, for the purpose of defining the consensus cohort below.

- C: score in [40, 55). Weak fit; several pillars fail.
- D: score in [0, 40). The framework's pillars fail systemically.
- F is reserved for stocks where the scoring engine could not produce a meaningful number due to data quality (missing pillars), and is treated separately in the backtest.

2.5 Cross-framework consensus

For each stock, we compute the seven framework scores and count the number of frameworks scoring the stock at B+ or better (score greater than or equal to 60). We call this the **bull count**, denoted `k` in [0, 7]. A stock with k equals 7 is one where all seven frameworks independently rate the company at B+ or better. A stock with k equals 6 has six lenses converging despite having different rubrics; a stock with k equals 1 has narrow framework-specific appeal.

We construct two views of the consensus distribution. The **per-bucket** view groups stocks by exact bull count k (separately for k=0 through k=7). The **cumulative** view groups by the threshold k greater than or equal to N (so the 5+ cumulative bucket pools stocks at k=5, k=6, and k=7). The per-bucket view shows the distribution; the cumulative view answers "which 'X+ or better' threshold should be applied?"

The score-based consensus threshold (B+ at 60) replaced an earlier verdict-based threshold ("framework yields a 'yes' verdict") in May 2026 because the verdict-based cohort sizes (typically 4 to 10 stocks at the all-7 tier) were too small for statistically meaningful comparison against the S&P 500. The score-based threshold produces cohorts of 30 to 80 stocks at the all-7 tier, which we treat as the minimum for an honest median estimate.

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3. Data and Universe

The fundamental data feed is Financial Modeling Prep (FMP) for income statements, balance sheets, cash flow statements, and computed ratios. Price history is sourced from FMP with cross-validation against the SPY benchmark series. The platform's coverage universe at the snapshot date of May 25, 2026 is approximately 12,500 US-listed tickers across NYSE and NASDAQ.

The backtest cohort is filtered to operating equities passing the following exclusions:

- Market capitalization greater than or equal to $500 million at the snapshot date (excludes micro-caps where ramp endpoints calibrated to mid-and-large-cap fundamentals systematically misbehave, and where price impact would dominate any real-money implementation).
- Instrument type is an operating equity (excludes ETFs, REITs, preferreds, bond funds, and insurance conglomerates whose capital structures are not comparable; this matches the universe filter applied across the seven frameworks since Buffett's pillars cannot meaningfully apply to a bond fund).

- Has at least one year of historical close-price data so the cohort can contribute to the one-year median; the five-year cohort requires five years of price data, which materially reduces the contributing sample for the long horizon.

After applying these filters, the May 2026 snapshot universe is **3,085 stocks**. Within this universe, the all-seven-frameworks-pass cohort (all seven frameworks scoring greater than or equal to 60 on the same stock simultaneously) is **47 stocks**, approximately 1.5 percent of the universe.

We deliberately do not include delisted securities in the universe. This is the survivorship-bias caveat documented in Section 5. Phase 3 of the platform's backtest engine, which uses quarterly point-in-time fundamental snapshots with delisting events preserved, is in development.

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4. Backtest Design

4.1 Setup

We implement what is best characterized as a current-grade lookback. Each stock in the universe is scored against the seven frameworks using fundamentals available as of the May 25, 2026 snapshot. For each stock, we compute its one-year, three-year, and five-year backward price return, defined as the percentage change between the closing price on the snapshot date and the closing price `N` years prior, dividend-unadjusted (returns are price returns, not total returns).

Per-stock returns are capped at +400 percent and floored at -100 percent. The cap is applied so that a single moonshot (a previously low-priced stock that ten-bagged over the five-year window) does not dominate cohort medians; the floor at -100 percent reflects the fact that a stock cannot decline by more than 100 percent (a delisted-to-zero stock realizes exactly -100 percent, although our universe excludes already-delisted stocks). Both bounds are documented on the public track-record page and in the JSON-LD Dataset schema served alongside it.

4.2 Cohorts evaluated

For each value of N in {1, 2, 3, 4, 5, 6, 7} we compute the cumulative cohort of stocks with bull count k greater than or equal to N. For each cohort and each horizon (1y, 3y, 5y) we compute the cohort's median return, mean return, percent positive (share of cohort members with strictly positive return over the horizon), and cohort size (number of stocks contributing at that horizon, which may be less than the headline cohort size for the 5y horizon if some cohort members IPO'd within the last five years and have less than five years of price history).

In parallel we compute per-framework standalone cohorts. The "Buffett-only cohort at A or A+" comprises stocks where the Buffett framework scores them at 70 or above (Buffett grade A or A+) regardless of how they score on the other six frameworks. We compute analogous standalone cohorts for the other six frameworks.

The benchmark is SPY's price return over the matching horizon. The S&P 500 is the conventional benchmark for US-listed equity strategies and SPY is the most-traded total-return-tracking instrument referencing it.

4.3 Statistic of choice

We lead with median return rather than mean return. The justification is empirical: cohort distributions in this universe are skewed by a small number of outliers (junk-rally winners cap returns can pull the mean of a 40-stock cohort up by 50 plus percentage points while leaving the median nearly unchanged). The median is what the typical stock in the cohort returns; the mean is dominated by the right tail. For a strategy that retail investors would implement by holding 5 to 30 names rather than the full cohort, the median is the more honest summary statistic.

We report both mean and median in the open Dataset alongside this paper. The 73.8 percentage-point headline outperformance is a median.

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5. Results

5.1 Headline result

In the May 25, 2026 snapshot, the cohort of stocks where all seven frameworks score at B+ or better simultaneously (k equals 7, the all-seven-frameworks-pass tier) contains n equals 47 stocks. The median five-year price return of this cohort is approximately **+73.8 percentage points above SPY's five-year price return** over the same window. 85 percent of the cohort posted positive five-year returns; the remainder posted negative five-year returns but no member of the cohort delisted within the window (a function of the survivorship-biased universe construction).

Approximately 1.5 percent of the 3,085-stock universe clears the all-seven bar on any given day. The bar is meant to be hard to clear and the resulting cohort is meant to be small. The 5+ cumulative tier (stocks where at least five frameworks score at B+ or better) is larger, with cohort sizes in the 150 to 250 range, and exhibits a smaller but still positive median outperformance over SPY.

The headline number is dated to the May 24, 2026 snapshot for the purposes of cross-surface consistency during a marketing window. As the cohort drifts day to day (one or two stocks moving across the 60-score threshold on a given framework), the live computation moves within a band typically described as +60 to +75 percentage points. Both the dated headline and the live snapshot come from the same scoring algorithm; the variation is cohort-composition drift, not methodological inconsistency.

5.2 Per-framework standalone cohorts

For comparison, we report the standalone five-year cohort performance of stocks scoring A or A+ on each framework individually (score greater than or equal to 70):

- **Buffett A/A+ standalone**: cohort sizes typically in the 80 to 140 range; median outperformance over SPY positive but materially smaller than the all-seven cohort.
- **Graham A/A+ standalone**: cohort sizes are small (the universe of stocks passing all of Graham's hard rules in the 2026 market is structurally tight); the cohort's median return is positive in absolute terms but trails SPY over the same window because the Graham lens is calibrated for deeply cheap balance-sheet plays which have not been the dominant return-driver of the past five years.
- **Fisher A/A+ standalone**: cohort tilts heavily toward asset-light businesses with proven process knowledge; median outperformance over SPY is positive over five years.
- **Lynch A/A+ standalone**: cohort tilts toward mid-cap growers; performance is more sensitive to one-year regime effects than to long-horizon fundamentals, but the five-year median is positive vs SPY.
- **Greenblatt A/A+ standalone**: cohort tilts to operating businesses with high ROIC and high earnings yield; per-Greenblatt's own published backtests this is the cohort with the strongest standalone single-framework long-horizon record.
- **Munger A/A+ standalone**: cohort sizes are small (the Munger framework is the strictest of the seven); the median return is positive and the dispersion is low (Munger's no-debt and no-binary-risk filters specifically reduce tail volatility).
- **T. Smith A/A+ standalone**: cohort tilts heavily toward consumer staples and software businesses with high FCF conversion; five-year median return is positive vs SPY.

The qualitative finding across these standalone results is consistent with the prior literature: each single-framework cohort can be characterized as positive and beating SPY on a five-year horizon in this dataset, but with a smaller and more dispersed effect than the consensus cohort. The convergence of all seven frameworks is what produces the magnitude of the headline outperformance.

5.3 Sector distribution

The all-seven-frameworks-pass cohort exhibits a sector distribution that reflects what the converged lenses select for. The dominant sectors are consumer staples, software and IT services, healthcare equipment and services, and selected financials. Sectors meaningfully underrepresented relative to the universe are deep cyclicals (materials, integrated oil and gas), heavily regulated infrastructure, and early-stage biotech.

This pattern is what would be predicted ex-ante from the framework-level exclusions. Buffett and Munger both pass on regulatory tail risk; Smith excludes cyclicals; Fisher excludes asset-heavy commodity businesses; Greenblatt's framework is calibrated against banks and utilities. The intersection of the seven frameworks therefore selects for what the literature would describe as durable cash-compounding businesses, often with brand or network-effect moats, operating in non-discretionary or recurring-demand end markets.

5.4 Limitations and biases

We disclose the following methodological limitations openly. Each is also disclosed on the public track-record page and in the platform's published methodology pages.

Survivorship bias. The universe consists of US-listed tickers active as of the snapshot date. Securities that delisted within the five-year window (including bankruptcies and acquisitions at par) are not represented. The standard fix is a point-in-time universe construction; the platform's Phase 3 backtest, which constructs a quarterly point-in-time snapshot and preserves delisting events, is in active development. The cohort returns reported here should be read as a directional signal characteristic of the cross-framework selection process, not as a tradeable strategy backtest.

Look-ahead bias. The grade is computed today against today's fundamentals and is then mapped onto historical price returns. The grade therefore implicitly knows the future state of the fundamentals at the time prices were realized. The standard fix is again a point-in-time backtest using only data available as of the trade date. The look-ahead bias most plausibly inflates the magnitude of the headline outperformance, since today's high-grade cohort by construction has the realized fundamental track record of the past five years. We treat the +73.8 percentage point figure as an upper-bound directional estimate; the point-in-time corrected estimate is expected to be smaller but still positive.

Transaction costs and price impact. Backtest returns are gross of transaction costs, bid-ask spread, slippage, and price impact. For the small all-seven cohort (n=47) and a small-dollar implementation these costs would be negligible; for an institutional implementation they would be material on the rebalance dates.

Dividend treatment. Returns are price returns. Total returns including reinvested dividends would be higher in absolute terms; the cross-framework cohort tilts toward dividend-paying compounders, so the absolute uplift from total-return measurement would be larger for the consensus cohort than for SPY by perhaps 1 to 2 percentage points per year.

Single-snapshot estimation. The headline is computed from a single snapshot date. Rolling-window estimation (computing the same statistic on each of, e.g., twelve quarterly snapshot dates and reporting the distribution of results) would provide a confidence band around the point estimate. We treat the +73.8 percentage point figure as a point estimate and disclose the day-to-day drift band of roughly +60 to +75 percentage points.

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6. Discussion

The empirical question this paper investigates is narrow: what does it select for when seven philosophically distinct value-investing frameworks all simultaneously score the same stock at B+ or better? The empirical answer is that the resulting cohort exhibits five-year price returns that exceed the S&P 500's five-year return by a wide margin in our snapshot, with the caveats in Section 5.4.

The mechanistic interpretation is that each framework encodes a different facet of "business quality at a reasonable price." Buffett encodes durable moat plus owner-friendly management plus reasonable valuation. Graham encodes statistical cheapness plus balance-sheet conservatism. Lynch encodes growth at a reasonable price. Greenblatt encodes capital efficiency plus cheapness. Munger encodes very high quality plus no debt. Smith encodes very high return on capital plus high FCF conversion. Fisher encodes growth runway plus process-knowledge depth. A stock that satisfies any one of these is a candidate for that lens. A stock that satisfies all seven simultaneously must have a combination of moat, conservatism, growth, capital efficiency, low leverage, and cash conversion that is hard to fake by optimizing any single underlying ratio.

The intersection acts as an ensemble. Each lens has its own false-positive mode (Graham finds value traps; Smith finds consumer brands at their peak; Greenblatt's pure-rules screen picks up structurally cheap stocks that turn out to have terminal issues a qualitative read would have caught). The intersection of seven lenses, each of which fires its false-positives on different stocks, materially reduces the joint false-positive rate. We hypothesize this is the primary mechanism producing the observed outperformance.

We do not claim that the ensemble is optimal. A larger ensemble (adding frameworks beyond the seven we implement) might produce a smaller intersection that is even more selective; a smaller ensemble (using a hand-picked subset of three or four) might produce a more practical cohort size at the cost of selectivity. Future work could investigate the marginal contribution of each framework to the ensemble.

A reasonable counter-hypothesis is that the all-seven cohort is selecting for backward-looking quality, that backward-looking quality has been the dominant return factor of the past five years, and that the result therefore reflects a regime effect rather than a robust feature of the consensus mechanism. We cannot fully refute this with a single five-year snapshot. Rolling-window estimation and the point-in-time Phase 3 backtest are the appropriate ways to address this counter-hypothesis. We note that each of the seven frameworks predates the past five-year regime by decades (Graham, 1934; Fisher, 1958; Lynch, 1989; Greenblatt, 2005) and that the result is therefore not the product of a framework calibrated on the test window.

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7. Reproducibility

The methodology and scoring engine are open and auditable. Specifically:

- The seven framework rubrics, the pillar weights, the ramp endpoints, and the deal-breaker caps are documented in source code at `src/lib/scoring/` and described in plain English at `https://invest-like.com/methodology/` and `https://invest-like.com/methodology/buffett-fit/`.
- The five-year track record page at `https://invest-like.com/track-record/` renders the live backtest output and exposes the underlying data via a JSON-LD Dataset schema (CC BY 4.0 licensed) embedded on the page.
- A public verdict API exists at `https://invest-like.com/api/public/verdict/[ticker]` returning the seven framework scores, grades, and consensus tier for any covered US-listed ticker.
- A public track-record API exists at `https://invest-like.com/api/public/track-record` returning the current cohort statistics.
- An OpenAPI specification at `https://invest-like.com/api/public/openapi.json` documents the full public API surface.

A third party with their own fundamental data feed can re-implement the scoring rubrics from the published documentation, apply them to their data, and reproduce the cohort definitions. With access to a comparable price history feed they can reproduce the cohort returns. We treat methodological reproducibility as a higher-priority research output than the headline number.

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8. Disclaimer

This paper documents a research methodology and a backtest result. It is not investment advice. It is not a recommendation to buy, sell, or hold any security. It is not personalised to any individual investor's circumstances, risk tolerance, time horizon, tax situation, or other relevant factors.

Past performance, including the cohort returns documented here, does not predict future returns. The methodology contains documented biases (survivorship, look-ahead) that plausibly inflate the magnitude of the headline result. A stock scoring at the highest cross-framework consensus tier today may underperform; a stock scoring at the lowest tier today may outperform. The scoring engine grades a stock's fit against documented frameworks; it does not forecast price.

Readers considering any investment decision should perform their own due diligence and consult a qualified financial advisor in their jurisdiction. The author is an independent researcher and is not a registered investment adviser in any jurisdiction.

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Author Bio

Zaid Ghazal is an independent researcher and the founder of invest-like (https://invest-like.com), a self-funded equity research platform based in Kiel, Germany. The platform grades every US-listed operating equity against the seven frameworks documented in this paper, publishes a live track record of the resulting cohorts, and exposes the underlying methodology in public source code, public APIs, and per-ticker methodology pages. The author is not a registered investment adviser. Contact: zaid@invest-like.com.

This paper documents methodology current as of May 25, 2026. The headline cohort statistics are dated to the May 24, 2026 snapshot for cross-surface consistency. Subsequent revisions of this paper will be posted as a new SSRN submission rather than as an amendment to this version; the asof date is the canonical version anchor.