# Formula Investing

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**Abstract**

This study evaluates the effectiveness of four popular investing formulas—the F-Score, Magic Formula, Acquirer's Multiple, and Conservative Formula—within a unified framework over an extensive period. Each formula generates significant raw and risk-adjusted returns, primarily by providing efficient exposure to well-established style factors. However, no single formula consistently outperforms across all metrics. The Acquirer's Multiple achieves the highest returns for top decile portfolios, the Conservative Formula leads in CAPM alpha and return spread, and the Magic Formula exhibits the highest remaining alpha after adjusting for common factors. While all formulas remain successful for concentrated long-only portfolios in the post-2000 period, we observe some performance decay relative to earlier periods, underscoring the need for continuous innovation in investing strategies.

**Keywords**: Quantitative Investing, F-Score, Magic Formula, Acquirer's Multiple, Conservative Formula

**JEL Classification**: G11, G12, G14

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## 1 Introduction

Investing formulas are easy-to-implement stock screeners that aim to provide instructions on how individual investors can beat the stock market. Among the most popular investing formulas are the F-Score by Piotroski (2000), the Magic Formula by Greenblatt (2006, 2010), the Acquirer's Multiple by Carlisle (2017), and the Conservative Formula by van Vliet and Koning (2017) and van Vliet and Blitz (2018). These formulas are based on different stock characteristics and implicitly or explicitly translate stock market anomalies into investable strategies. More specifically, the F-Score by Piotroski (2000) is the sum of nine binary signals measuring the financial strength of a firm. It distinguishes financially weak from financially strong firms among value stocks. The central idea behind Greenblatt's Magic Formula is to buy high-quality companies at attractive prices, identified by combining a company's return on capital with its earnings yield, while the Acquirer's Multiple focuses solely on a stock's enterprise multiple. Finally, the Conservative Formula selects low-volatility stocks that exhibit the highest momentum and net payout yield.

While some studies have revisited the investing formulas for more recent samples or other markets, a comprehensive and thorough joint analysis of these investment formulas has not been conducted. This paper fills this gap by presenting empirical evidence on the efficacy of these investing formulas for the U.S. market from 1963 to 2022. Our analysis is based on the comprehensive CRSP/Compustat universe, but we exclude microcaps to dismiss concerns that tiny stocks, often illiquid and hard to trade, drive the results. To investigate the profitability of the investing formulas, we sort stocks into decile portfolios and compute their raw and risk-adjusted performance. Moreover, we regress the top-minus-bottom return spreads on common asset pricing factors to determine how much of the formulas' performance is attributable to their exposure to these factors. Finally, we adopt a "do-it-yourself" investor's perspective by forming concentrated long-only portfolios of the 40 best-ranked stocks for each formula and evaluating their performance in the post-2000 period.

Our main findings are summarized as follows. First, we find that all formulas lead to near-monotonically increasing returns when sorting stocks into decile portfolios. As a result, the top portfolios outperform both the market and the bottom portfolios. Furthermore, the top-minus-bottom portfolios exhibit significant annual raw returns ranging from 5.6% to 6.4%, while the CAPM alphas range from 7.0% to 12.2%. While the formulas show strong performance over the full sample, they also exhibit periods of pronounced underperformance and indications of performance decay in the post-2000 period. Second, factor-spanning tests reveal that the formulas achieve this outperformance primarily by providing efficient exposure to established asset pricing factors such as value, profitability, and momentum. Third, concentrated long-only portfolios of the 40 top-ranked formula stocks also outperform the market in the post-2000 period, both in terms of raw and risk-adjusted returns. However, all investing formulas suffer from substantial relative drawdowns during the 2018-2020 period. Finally, we document that no single investing formula dominates across all performance evaluation metrics. In the decile analysis, the Acquirer's Multiple exhibits the highest return for the top portfolio, while the Conservative Formula has the highest top-minus-bottom return and CAPM alpha spread. Conversely, the Magic Formula achieves the

highest remaining alpha when controlling for common asset pricing factors. For concentrated capped-value-weighted portfolios of 40 stocks in the post-2000 period, the Magic and Conservative Formulas offer the highest raw and risk-adjusted performance, respectively.

This study contributes to the literature in at least three aspects. First, it adds to the stream of literature that investigates the performance of investment formulas following the original publication. For example, Piotroski and So (2012) and Walkshäusl (2017) confirm the profitability of the F-Score in conjunction with the book-to-market ratio for the U.S. and Europe, respectively. Greenblatt (2010) and Larkin (2011) confirm the initial findings of Greenblatt (2006), showing that the Magic Formula significantly outperforms the broad U.S. market. The enterprise multiple, which is the valuation metric used in the Acquirer's Multiple by Carlisle (2017), emerges as the winner in a horserace of different valuation measures in Gray and Vogel (2012), while Loughran and Wellman (2011) document positive results when using EBITDA instead of EBIT. Finally, van Vliet and Blitz (2018) confirm the findings of van Vliet and Koning (2017) for the U.S. market, as well as for Japan, Europe, and emerging markets, and Walkshäusl (2020) for the Eurozone. However, none of these studies investigates more than one formula over an extensive period.

Second, Chordia et al. (2014), Green et al. (2017) and Blitz et al. (2023a) document a substantial decay in the performance of single-factor, linear model, and machine-learning model strategies in the U.S. during the post-2000 period. The authors argue that increased liquidity and trading activity in the post-decimalization period caused this decline. While the investigated investing formulas still outperform the market in the post-2000 period in terms of both raw and risk-adjusted returns, we also observe a decline in performance compared to the pre-2000 period. These findings indicate that investing formulas are not immune to this performance decay and may need continuous innovation (cf., Swade et al., 2024).

Finally, the investigated investment formulas are relatively easy to implement, which distinguishes them from more complex and sophisticated models, such as machine-learning prediction models, which have become popular in recent years, cf., Rasekhschaffe and Jones (2019), Gu et al. (2020) or Hanauer and Kalsbach (2023). Although these more complex models typically provide higher gross returns (cf., Blitz et al. 2023a), they also entail higher turnover and transaction costs. Moreover, investors may encounter additional investment barriers, including limited access to the necessary data, missing infrastructure to process the data, or the inability to execute the resulting signals in a timely and efficient manner (cf., Blitz et al. 2023b). These more sophisticated models present therefore only genuine opportunities for those investors who are able to overcome these challenges. In contrast, the investigated investing formulas provide investors with efficient exposure to established factor premiums and are relatively easy to implement.

The remainder of this study is structured as follows: Section 2 describes the data, investing formulas, and the common approach to testing and comparing the investing formulas. Section 3 presents the empirical results, and Section 4 concludes.

## 2 Data and Methodology

### 2.1 Sample Sources and Data Criteria

In our study, we employ common data sources to create one unified empirical framework. Price and return data comes from the Center for Research in Security Prices (CRSP), and annual accounting data comes from Compustat. We include all U.S. common shares (codes 10 and 11) that are traded on one of the three major U.S. exchanges, which are the NYSE, NYSE MKT (formerly AMEX), or the NASDAQ. Additionally, we incorporate delisting returns from CRSP. If the delisting return is unavailable and the delisting code indicates that the company was delisted for reasons other than fraudulent behavior, we set the delisting return to -30%, following Shumway (1997).

For the annual accounting data, we adopt the approach of Jensen et al. (2023b) to modify and calculate different accounting items if they are not directly available in the database.[1] If a firm's book equity is negative or zero, we set it to missing, as is commonly done when working with book-to-market ratios (see, e.g., Fama and French 1992). We exclusively use annual accounting to mitigate the influence of seasonal fluctuations often associated with quarterly data, as suggested by Dechow et al. (1998). Furthermore, we impose a minimum lag of six months after the financial year-end, following Fama and French (1993). Financial companies are excluded since all formulas except the Conservative Formula rely on some accounting measures, which are not available or meaningfully defined for financials.

Our sample period spans from July 1963 to December 2022, chosen because July 1963 is the typical starting point for factors using accounting data. We exclude microcaps, defined as stocks with market capitalizations below the 20th percentile of NYSE market capitalization, to avoid concerns that our results are driven by small, illiquid stocks (cf., Fama and French, 2008 and Hou et al., 2020). Although the excluded micro stocks represent 58% of all stocks, they constitute only 3% of the total market value. Thus, the sample consists of companies large and liquid enough to invest in, with a minimum market capitalization of USD 450 million and an average of USD 30,824 million as of December 2022. Moreover, the average number of stocks in our unified sample is 921, ranging from a low of 298 firms in July 1963 to a high of 1,163 in April 2002. Factor returns are obtained from public data libraries.[2]

### 2.2 Investing Formulas

#### 2.2.1 Piotroski F-Score

The F-Score, as published by Piotroski (2000), is the sum of nine binary financial signals and aims to separate good and bad investments among high book-to-market (value) stocks. For

[1] The exact table for all data items and the Compustat codes can be found in Appendix A1a.

[2] The Fama and French factors, momentum factor, and the one-month risk-free rate are from Kenneth R. French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html. Additionally, the monthly updated value factor is from https://www.aqr.com/Insights/Datasets/The-Devil-in-HMLs-Details-Factors-Monthly.

the replication of the score, we follow the original description of Piotroski (2000) and the approach of Jensen et al. (2023a) for the handling of data items. Thus, the score is the following:

$$\textit{F-Score} =$$

$$F_{ROA} + F_{CROA} + F_{\Delta ROA} + F_{ACC} + F_{\Delta LEV} + F_{\Delta LIQ} + F_{EQIS} + F_{\Delta GM} + F_{\Delta Turnover}$$

With:

(1) $F_{ROA}$ being one if the ROA in year t is positive and zero otherwise. ROA is calculated as the net income excluding unusual items (item IB in Compustat) in year t divided by the total assets (item AT) at the end of year t-1.
(2) $F_{CROA}$ being one if the operating cash flow return on assets in year t is positive or zero if it is negative. With the CROA being the operating cash flow (item OANCF) in year t, it is again scaled by the total assets in year t-1.
(3) $F_{\Delta ROA}$ being one if the ROA in year t is greater than the ROA in year t-1.
(4) $F_{ACC}$ being one if CROA is bigger than ROA and zero otherwise.
(5) $F_{\Delta LEV}$ being one if the leverage of the firm did not increase from year t-1 to year t and zero otherwise. We calculate the leverage by dividing non-current financial debt (item DLTT) by the average total assets. Average total assets are the sum of AT in year t plus AT in year t-1 divided by two.
(6) $F_{\Delta LIQ}$ being one if the current ratio increased from year t-1 to year t and zero otherwise. We calculate the current ratio by scaling the current assets (item CA) by the current liabilities (item CL).
(7) $F_{EQIS}$ being one if the company did not issue any kind of equity (item EQIS) and zero otherwise.
(8) $F_{\Delta GM}$ being one if the gross margin increased and zero otherwise. The gross margin is defined as the gross profit (item GP) in year t divided by the net sales (item SALE) in year t.
(9) $F_{\Delta Turnover}$ being one if the asset turnover increased from year t-1 to year t, and zero otherwise. With the asset turnover being the net sales in year t scaled by the assets in year t-1.

We follow the approach of Jensen et al. (2023a) and exclude all companies for which any of the nine signals cannot be calculated, except for the equity issuance. If this variable is missing, we set it to zero, as it is rarely available in earlier years prior to 1972.

Piotroski (2000) uses the F-Score alongside the book-to-market ratio (B/M) to separate financially weak and financially strong firms among value stocks. More specifically, his long portfolio consists of the cheapest quintile of value stocks with an F-Score above seven. To ensure comparability across all formulas, we combine these steps into a single formula score. First, we rank all companies by their B/M ratio, with the highest B/M receiving the best rank. We then rank companies by their F-Score, assigning the same rank to those with the same number of positive signals. We combine these ranks to create one score for each company, ensuring the best-ranked companies are both affordable (high B/M) and financially strong (high F-Score). In this paper, the term F-Score refers to this combined ranking. Companies are

ranked in ascending order based on their final score, with the best total score receiving the lowest rank.

### 2.2.2 Magic Formula

The Magic Formula, developed by Greenblatt (2006), combines two key metrics: earnings yield (EY) and return on capital (ROC). The formula ranks stocks independently based on their EY, which measures relative cheapness, and their ROC, which gauges operational efficiency. EY is calculated as operating income after depreciation and amortization but before interest and taxes, divided by enterprise value (EV). EV is defined as the higher of (i) market capitalization plus preferred stock (PSTKRV), minority interest (MIB), and net debt (ND, total debt minus cash and equivalents) or (ii) one, to avoid negative values (cf., Appendix A1 for details).

EV is adjusted to include preferred stock and minority interest due to their debt-like features and offsets cash and equivalents against debt, as they could be used to settle debt. This simplified approach avoids complex assumptions about operational cash requirements, facilitating relative comparisons among firms. A floor value of one for EV prevents distortions in the ranking due to potential negative EV.[3]

ROC is computed as EBIT divided by tangible capital employed, defined as net working capital plus net fixed assets, excluding intangibles such as goodwill (Greenblatt 2010). This approach ensures the capital base reflects the actual capital needed for daily operations. To avoid positive ratios from negative operating earnings, invested capital (IC) is calculated as the maximum of (i) current operating working capital (COWC) plus non-current operating fixed assets (NCOFA) or (ii) one (cf., Appendix A1b for details).

This methodology aligns with Greenblatt's (2006, 2010) original description and is consistent with the definition of the accounting items as in Jensen et al. (2023b). The Magic Formula aims to identify "good" companies available at "bargain" prices, predicting stock price performance effectively. While an exact replication of Greenblatt's formula is challenging due to limited insight into the precise calculation of invested capital, the approach ensures consistency and comparability across different companies (cf., Blij, 2011 or Larkin, 2011).

$$Magic\ Formula\ Rank = EY\ Rank + ROC\ Rank$$

The final Magic Formula score combines the rankings for EY and ROC. For example, if a company has the highest EY and ranks third in ROC, its combined score would be four. The ultimate ranking is based on this combined score, ensuring that the selected companies are both affordable and financially strong.

[3] The handling of firms with negative EV is not described, nor by Carlisle 2017 nor by Greenblatt 2006, 2010, leaving some room for interpretation.

### 2.2.3 Acquirer's Multiple

The Acquirer's Multiple, as described by Carlisle (2017), is calculated by dividing a company's enterprise value (EV) by its operating earnings. Therefore, the Acquirer's Multiple is the inverse of the earnings yield (EY) used in Greenblatt's Magic Formula (2006, 2010) and the only formula that is based only on one signal. We include firms with negative earnings, assigning them low rankings, and later evaluate whether these firms perform worse than highly ranked companies. Additionally, companies with a negative EV are included, but their EV is set to one, resulting in a very high EY if earnings are positive. This approach rewards companies with substantial cash relative to their debt levels and market capitalization.

Carlisle (2017) suggests that firms with negative EVs are attractive investments but does not address the mathematical challenges this presents. To remain consistent with the original study, we retain these firms in the sample and assign them high rankings by manipulating the denominator. However, alternative approaches, such as excluding companies with negative earnings or negative EV, have been used in other studies, like Loughran and Wellman (2011), who examined the relationship between the enterprise multiple and stock returns.

### 2.2.4 Conservative Formula

The Conservative Formula, proposed by van Vliet and Koning (2017) and extensively tested by van Vliet and Blitz (2018), combines three distinct market anomalies: low-volatility, momentum, and net payout yield (NPY). The original method involves two steps: first, dividing the 1,000 largest companies into two groups based on historical volatility; second, selecting the 100 best-ranked stocks according to the average rank of price momentum and NPY from the low-volatility group. Unlike other formulas, the Conservative Formula does not require accounting data, allowing for tests before 1963 and across different markets.

For consistency with the other formulas, we convert the three components into one combined score, allowing us to rank all companies in the sample without preselecting based on volatility or size. Each component is weighted equally, contributing one-third to the final score. [4] The Conservative Formula score is calculated as follows, based on descriptions by van Vliet and Blitz (2018):

$$Conservative\ Formula\ Rank =$$

$$1/3\ \times Volatility\ Rank + 1/3\ \times\ NPY\ Rank + 1/3\ Momentum\ Rank$$

With:

(1) Volatility Rank: Based on 36-month historical return volatility, calculated as the standard deviation of monthly stock returns over the previous 36-months, ranked in ascending order.
(2) NPY Rank: Defined as the descending ranking according to the net payout yield (NPY). NPY is the sum of dividend yield and share buyback yield minus share

[4] In unpublished results, we find that this simple weighting comes close to the original implementation of the formula.

issuance yield. NPY can be computed as the part of the total stock return (*R)* not captured by the growth rate in market capitalization (*MC*):

$$NPY = R_{(t-13,t-1)} - \log(MC_{t-1}/MC_{t-13}).$$ [5]

(3) Momentum Rank: Based on cumulative monthly return for the 11-month period ending one month before the portfolio formation, ranked in descending order.

Finally, we sort all stocks in ascending order based on the combined Conservative Formula rank, with a lower rank considered favorable, consistent with the ranking methodology used for the other formulas.

### 2.3 Testing the Formulas

After gathering and preprocessing the data, we can test the investigated formulas. To ensure comparability across the different formulas, we follow a uniform approach for different financial metrics, portfolio creation, and the use of accounting information. Consequently, this leads to differences from the originally proposed strategies, making comparisons to the reported results from the formula creators only partly possible.[6]

We test the investing formulas in two ways. First, we investigate the investing formulas via sorts in decile portfolios. Thereby, we allocate stocks into decile portfolios based on all stocks. We do not use NYSE breakpoints as done in Hou et al. (2020), as we already exclude microcaps. Basing the breakpoints on the full sample ensures an equal number of stocks in each decile and, hence, similar diversification effects. We report average returns for the decile portfolios and the top-minus-bottom decile portfolio. Furthermore, we assess the strategies through a factor lens by regressing them on the five Fama-French factors plus momentum. This approach follows the standard testing procedure of asset pricing studies and ascertains the extent to which the formula performance is attributable to common asset pricing factors. Finally, we also compare the strategies' performance over time.

Second, we take the perspective of a "do-it-yourself" investor by forming concentrated long-only portfolios of the 40 top-ranked stocks for each of the different formulas and evaluate their performance in the post-2000 period. This assessment aims to determine whether outperformance is indeed possible, significant, and implementable for retail investors who may be restricted in their ability to short-sell.

Portfolios are updated at the end of each quarter, using the latest price and stock data at formation and yearly accounting data with a reporting lag of at least six months. Rankings for each firm remain constant until the end of the next quarter. For the main analysis, we compute capped-value-weighted monthly returns following Jensen et al. (2023b), capping the weight

[5] This definition is the composite equity issuance (cf., Daniel and Titman 2006 or Hanauer and Lauterbach 2019) multiplied by -1. Share repurchases, dividends, and other actions that take cash out of the firm increase the yield measure, while seasoned issues, employee stock option plans, and share-based acquisitions decrease the yield measure.

[6] In unpublished results, we try to replicate the individual formulas as closely as possible and find similar results as in the original studies.

of individual firms in value-weighted return calculations at the 80th percentile of NYSE market capitalization. This approach ensures that small firms contribute proportionally and prevents a few mega-cap stocks from dominating the results. Equally-weighted returns are included in Section 3.3 as well as reported in the appendix.

## 3 Empirical Results

The objective of this empirical analysis is to compare the formulas in terms of risk and consistency of performance. We test for statistical significance using decile portfolios in a classical asset pricing framework, but also test performance over time. Furthermore, we test concentrated long-only portfolios in the 21st century to see if individual investors could still beat the market by implementing these strategies.

### 3.1 Full sample decile portfolios

The firms are ranked according to the formula score, facilitating their separation into deciles. Thereby, the first decile consists of the best-ranked firms, and the tenth decile comprises those ranked at the bottom of the stock universe. Table 1 presents the annualized excess return of the deciles over the risk-free rate for the four investing formulas.[7]

[Table 1 about here]

When we investigate the patterns in the decile sorts, a clear trend emerges. The returns of the deciles follow a nearly monotonic pattern, with increasing returns from the bottom to the top decile. These results confirm the patterns documented in Piotroski (2000) and Greenblatt (2006, 2010). Moreover, the outperformance of the top decile over the bottom deciles is significant for all formulas and ranges from 5.63% for the F-Score to 6.44% for the Conservative Formula. This outperformance cannot be explained by the CAPM, with all remaining alphas being statistically significant at the 1%-level and ranging even from 7.00% for the Magic Formula to 12.21% for the Conservative Formula. These findings support the original claims of the formula proponents, which holds true for capped value-weighted returns and in a sample without microcaps.[8]

In terms of formula comparison, the raw returns of the top decile of the Acquirer's Multiple are superior to those of the other formulas for the full sample period. This evidence supports Carlisle's (2017) claim that profitability, as considered by Greenblatt (2006, 2010), does not necessarily improve results, and the only important metric is the price at which a company can be purchased. In terms of the top-minus-bottom return difference, however, it does only show a slightly better performance with lower significance. Due to the very low performance

[7] Table A2 in the appendix shows more detailed performance statistics for the decile sorts, also including standard deviation, Sharpe ratio, CAPM beta, and CAPM alpha.

[8] The results for equally-weighted portfolio presented in Table A3 in the appendix show similar results.

of the bottom decile, the Conservative Formula offers the highest return difference of the formulas, and it has the highest and strongest CAPM alpha.

### 3.2 Performance through a factor lens

After assessing the formulas' long-term performance, we next measure the extent to which their performance is attributable to common asset pricing factors. Therefore, we regress their top-minus-bottom decile returns against established asset pricing models. The investigated asset pricing models are the CAPM, the Fama and French (1993) three-factor model (FF3FM), the three-factor model augmented with the momentum factor as in Carhart (1997) (FFC4FM), the Fama and French (2015) five-factor model (FF5FM), and the five-factor-model augmented with momentum (FF6FM). All multi-factor models use the monthly updated value factor as proposed in Asness and Frazzini (2013), which uses current market data and is hence more in line with the formula construction. Furthermore, Barillas et al. (2020) and Hanauer (2024) show that a six-factor model with a monthly updated value factor and a momentum factor dominates other factor models. The results for the full sample period from 1963 to 2022 are summarized in Table 2.

[Table 2 about here]

Panel A of Table 2 shows that the CAPM alpha for each formula is significant at the 1%-level when compared against the market risk premium, measured as the value-weighted performance over the risk-free rate of our final stock universe in the study, witnessing *t*-statistics varying from 3.73 to 5.41. Also the Fama and French (1993) three-factor model (FF3FM), which adds size (SMB) and value (HML) factors to the market factor, is not able to explain the performance of the top-minus-bottom portfolios as all alphas remain significant at the 1%-level. The highest reduction of alpha can be observed for the F-Score and the Acquirer's Multiple, as these formulas exhibit the highest value exposure. The F-Score directly incorporates the B/M ratio by design, while the EY in the Acquirer's Multiple is a value metric correlated to the B/M ratio that underlies the HML factor. For the Conservative Formula the alpha even increases, which can be partly attributed to the significant negative exposure to the SMB factor.

For the third model, the Carhart (1997) four-factor model (FFC4FM), which adds an additional momentum factor to the FF3FM, only the alpha of the Magic Formula and Acquirer's Multiple top–bottom portfolios are still significant at the 1%-level. For both formulas, the negative exposure to the momentum factor even increases the alpha. For the Conservative Formula, the addition of the momentum factor explains a significant part of the alpha. This is expected as momentum is also embedded into the formula itself, but it must be noted that the momentum and value factors also profit from monthly portfolios, while we use quarterly updated portfolios.

The Fama and French (2015) five-factor model (FF5FM), which also includes profitability (RMW) and investment (CMA) factors, can explain the alpha of the F-score and the Acquirer's

multiple. These formulas offer investors efficient exposure to the five-factor model and can be labeled as value/quality strategies. Still, some alpha remains, although not statistically significant. The Magic Formula and the Conservative Formula also exhibit positive exposure to the value and quality factors, but their alphas cannot be fully explained. Even though the Magic Formula has a large and significant weight on the RMW factor, it is not enough to explain the entire outperformance.

For our final model, the FF5FM augmented with momentum (FF6FM), all alphas are close to zero, except for the Magic Formula. The alpha for the Magic Formula remains statistically significant at the 1%-level, also due to its negative exposure to the momentum factor. Consequently, the formulas give investors an efficient factor exposure to some of the most established factors from the asset pricing literature.

Panel B presents the factor betas against the five-factor model plus momentum. All formulas show negative exposure to the market factor, which means that the top portfolio, compared to the bottom portfolio, is relatively more tilted to defensive low-beta stocks, whereas the bottom portfolio is relatively more tilted to cyclical high-beta stocks. The Conservative Formula is the most defensive, with a market beta of -0.48, whereas the other formulas have betas around -0.10.

The F-score and Acquirer's multiple have positive size tilts (SMB), which means the performance tends to be better during times when small caps outperform. The Magic Formula is neutral, whereas the Conservative Formula has a significant negative SMB exposure. Large stocks tend to have lower volatility, and more mature firms that are bigger and more stable tend to pay back more capital to shareholders due to limited growth prospects, according to Bulan and Yan (2010).

All formulas exhibit positive exposure to value (HML), with the Acquirer's Multiple and the F-Score having the highest loadings. The Acquirer's Multiple focuses solely on cheap companies, even if it is measured by earnings instead of book equity, and the F-Score directly incorporates the B/M ratio. For the Magic Formula, the exposure is slightly lower, yet present, due to the EY component. For the Conservative Formula, the positive value exposure can be attributed to the net payout yield component, which is consistent with van Vliet and Blitz (2018), who report a positive HML exposure in the subperiod from 1963 to 2016.[9]

While all formulas are positively correlated to the profitability (RMW) factor, the Magic Formula and the Acquirer's Multiple exhibit the highest exposure. The exposure of the Magic Formula can be explained by the explicit profitability component of the formula. Nevertheless, the remaining alpha suggests that its profitability definition, ROC, is a superior profitability measure than the one of the RMW factor. The Acquirer's Multiple, on the other hand, has profitability not explicitly built into its formula. Thus, the cause for the exposure comes from the earnings yield, where the operating profit is the numerator, hence reflecting profitability. The Conservative formula has profitability implicitly embedded through payout

[9] The full sample HML exposure in van Vliet and Blitz (2018) is negative due to a highly negative correlation during the 1930s.

yield, whereas the F-score rewards firms that have positive accounting and cash returns on assets.

Both, the Magic Formula and the Acquirer's Multiple have nearly no weight on the investment factor (CMA), but the F-Score and especially the Conservative Formula do. The CMA factor is long in firms that invest conservatively and short in firms that invest aggressively. The Conservative Formula rewards companies that payout capital in the form of dividends or common stock repurchases, and both formulas penalize firms that do issue equity. Firms that do issue equity tend to increase investments in the subsequent period, according to Fama and French (2005) and Lyandres et al. (2008). Further, Aharoni et al. (2013) find that the change in shares outstanding is a predictor of future investments.

Except for the Conservative Formula, which has momentum built into its formula, and a small momentum beta for the F-Score, the other formulas have negative exposure to the momentum factor. This can be explained by the fact that companies with a low market capitalization in relation to their operating earnings or book equity often exhibit negative momentum. This indicates that, all else equal, a positive or neutral exposure to momentum would increase the performance of these strategies as this momentum premium is large and significant over time.

### 3.3 Performance through time

The full-sample period consists of almost 60 years of data, and we will test for consistency over time. Figure 1 displays the cumulative compounded performance of the top and bottom deciles divided by the cumulative compounded performance of the market per investing formula.[10]

[Figure 1 about here]

The analysis again reveals that all top decile portfolios outperform the market during the sample period while all bottom decile portfolios underperform the market. Thereby, the total return spread of the Conservative Formula is more driven by the bottom decile. For the other formulas, however, the top decile portfolios contribute more to the total return spread than the bottom portfolio. Furthermore, all top decile portfolios underperform the market during the run-up of the "dot-com bubble" between 1998 and 2000 and during the "Quant Winter" between 2018 and 2020. Finally, for all formulas, the outperformance of the top decile has flattened out over the 21st century. Hence, we conclude that the formulas show strong performance over the full sample but also exhibit periods of underperformance and some signs of performance decay. This conclusion supports Greenblatt's (2010) point that the strategy may underperform in the short term but works in the long run, requiring investor discipline but also the importance of continuous factor innovation (cf., Swade et al., 2024).

[10] Figure A1 in the Appendix also shows the cumulative compounded performance of the top decile divided by the cumulative compounded performance of the bottom decile per investing formula.

### 3.4 Do it yourself portfolios in the post-2000 period

Evidence from the previous long-short analyses indicates that the formulas have predictive power on stock returns. Still, this standard academic approach requires shorting, and the results over time also revealed a weakening of alphas after 2000. Therefore, we apply a "do-it-yourself" perspective on all four formulas.

Table 3 presents the performance summary statistics for concentrated long-only portfolios of the 40 top-ranked stocks per investing formula, both for capped-value-weighted and equally-weighted portfolios from January 2000 to December 2022.[11] The results reveal several key insights into the effectiveness and risk profiles of each formula. We always start with the results for the value-weighted portfolios and mention differences for the equal-weighted portfolios.

[Table 3 about here.]

The Piotroski F-Score shows an annualized compounded return of 13.2% with a Sharpe ratio of 0.59, thereby outperforming the market with a return of only 7.2% and a Sharpe ratio of 0.43. However, it suffers from the highest maximum drawdown of 57.5%, suggesting higher risk during market downturns, as also highlighted by its market beta of 1.19. Nevertheless, the F-Score portfolio still exhibits a CAPM alpha of 5.8%. The performance of the equal-weighted portfolio is slightly higher but overall conclusions remain the same. The CAPM alpha, however, decreases when measured against an equally-weighted market.

The Magic Formula shows the highest annual return of 15.8% with a Sharpe ratio of 0.69, indicating strong performance with moderate risk. Its maximum drawdown is 50.6%, which is the second lowest among the formulas but still higher than the one of the market of 44.1%. The CAPM alpha of 7.8% further underscores its strong performance, with a beta of 1.20, indicating again slightly higher market risk. Again, we see a slightly better performance for the equal-weighted portfolio, but the overall tendencies are similar.

The Acquirer's Multiple provides an annual return of 14.2% and a Sharpe ratio of 0.57, with a substantial drawdown of 53.6%. For the value-weighted portfolios it has a CAPM alpha of 6.0%. Its beta of 1.41 indicates that overall more cyclical stocks are selected, which also increases volatility and lowers the Sharpe ratio. We see the biggest improvement when switching to the equal-weighting, for which the Acquirer's Multiple even surpasses the performance of the Magic Formula but with a lower Sharpe Ratio and CAPM alpha.

The Conservative Formula offers the lowest annual return of 11.4% among the formulas but still outperforms the market and excels in risk-adjusted performance with a Sharpe ratio of 0.78 and the lowest maximum drawdown of 40.1%. Its CAPM alpha of 5.8% and a notably low beta of 0.66 underscore its defensive characteristics, making it an attractive option for risk-

[11] Figure A2 in the appendix shows that our conclusions remain similar for different portfolio sizes.

averse investors or to combine this formula with a high-beta strategy. Similar conclusions hold for the equal-weighted portfolio.

Table 4 presents the 23 annual returns of the four investing formulas compared to the market average to shed more light on performance. The bearish market years from 2000 to 2002 were among the best for formula investing. All formulas showed strong relative performance, beating the market, with 2001 being particularly strong for the Magic Formula. The bullish years from 2003 to 2006 were favorable for all formulas with limitations for the Conservative Formula, which was lagging the market during the recovery in 2003.

[Table 4 about here.]

In 2007, formula investing faced challenges as all formulas lagged behind the market, with the Acquirer's Multiple performing notably poorly, underperforming the market by nearly 15%. This difficulty in 2007 aligns with broader struggles in quant investing, as discussed by Khandani and Lo (2011). During the stock market crash of 2008, the Conservative Formula proved effective in limiting losses, whereas the other formulas declined more than the market average.

From 2009 to 2014, the formulas generally performed well, except for 2012, when all lagged the market, except for the F-Score. In 2015, formulas generally underperformed, except for the Conservative Formula, which showed strong absolute and relative performance. This trend reversed in 2016 when all strategies except for the Conservative Formula, which nearly mirrored the market return, strongly outperformed the market. During the period 2017-2020, most formulas struggled, especially the F-Score, reflecting the "Quant Crisis of 2018-2020" (cf., Blitz, 2021). The years 2021 and 2022 were again strong for formula investing, with all four formulas showing good absolute returns for 2021 and a resilient relative performance for 2022.

Finally, Panel A of Figure 2 presents the absolute drawdowns of the strategies and the market, and Panel B presents the relative drawdowns compared to the market. While the absolute drawdown analysis in Panel A reveals that the strategies tend to decline with the overall market, they sometimes experience less severe drawdowns, as in 2000-2002 or 2022, but sometimes even more severe, as in 2008/2009, 2015/2016, or 2020. We observe the deepest drawdowns of more than -50% for the Acquirer's Multiple and the F-Score in 2009 and 2020, respectively. The Conservative Formula, as the most defensive strategy, remains most resilient against market crashes and, even in a concentrated long-only strategy, generally experiences lower drawdowns than the general market, with the exception of the COVID-19 crash in 2020.

[Figure 2 about here.]

Panel B shows that the investing formulas suffer only from limited relative drawdowns before 2007 but exhibit rather high relative drawdowns during 2018-2020. Again, the Acquirer's

Multiple and the F-Score are exposed to the biggest pain. This underperformance mainly stems from their high exposure to the value premium, which suffered from an extreme widening of valuation spreads over this period (cf., Blitz and Hanauer, 2021). By the end of 2022, all formulas have partly but not yet fully recovered from these losses.

### 3.5 Discussion

The findings of this study generally align with previous research and the claims made by the creators of the original formulas. The F-Score strategy showed a return difference of 5.6% for the top and bottom deciles. This difference is smaller than Piotroski's (2000) 23.0%, which can be explained by the additional years considered, alternative portfolio construction, the exclusion of microcaps, and different handling of delisting returns. In particular, the F-Score struggled in the more recent 2017-2020 period.

The Magic Formula, as demonstrated in Greenblatt (2006, 2010), effectively generates market outperformance and explains the cross-section of average stock returns. The return difference between the top and bottom decile cannot be fully explained by the Fama and French (2015) five-factor model. The raw returns reported here are lower than those originally reported by Greenblatt but consistent with Carlisle's (2017) back-test results.

The study could not confirm Carlisle's (2017) assertion that the profitability dimension (ROC) in the Magic Formula lowers returns compared to the Acquirer's Multiple. The highest-ranked Acquirer's Multiple decile outperforms the Magic Formula, but concentrated portfolios show better raw and risk-adjusted returns with the inclusion of ROC. These findings are in line with Novy-Marx's (2013) that profitability measures improve value strategies.

The results of the Conservative Formula do not fully match the findings of van Vliet and Blitz (2018), mainly due to methodological differences. However, the main points of their research are validated: the Conservative Formula provides effective exposure to established asset pricing factors, achieves high risk-adjusted returns, maintains lower volatility, and outperforms the market on a cumulative basis due to lower drawdowns.

## 4 Conclusion

This study evaluates the effectiveness of four popular investing formulas—the F-Score, Magic Formula, Acquirer's Multiple, and Conservative Formula—over an extensive period from 1963 to 2022 for the U.S. market. The findings indicate that each formula generates significant raw and risk-adjusted returns, outperforming the market primarily by providing efficient exposure to value and quality factors. The Conservative Formula stands out as the most distinct strategy, offering positive momentum exposure and consistently low volatility, making it the most defensive strategy among the four.

The study confirms that all formulas exhibit predictive power in the cross-section of stock returns. However, no single formula consistently dominates across different performance metrics. The Acquirer's Multiple achieves the highest returns for top-decile portfolios, while the Conservative Formula leads in CAPM alpha and return spread. After adjusting for established asset pricing factors, the Magic Formula displays the highest remaining alpha.

The Magic Formula and Conservative Formula are particularly effective in the post-2000 period, especially in concentrated long-only portfolios. The Magic Formula demonstrates strong performance with moderate risk, achieving the highest raw returns among the formulas for capped-value-weighted portfolios. Conversely, the Conservative Formula excels in risk-adjusted performance, with the lowest maximum drawdown and a notably low beta.

When compared to the existing literature, this study's findings align with previous research on the profitability of these formulas. All formulas continue to generate market outperformance, although the returns tend to be lower than the original findings, primarily due to the exclusion of microcaps, the inclusion of out-of-sample years, and methodological differences.

Overall, this study demonstrates that formula-based investing can still generate market outperformance, providing investors with efficient exposure to well-documented factor premiums. These strategies thus offer relatively easy-to-implement options for investors but also require investor discipline as these strategies may underperform in the short term. As the effectiveness of these formulas has weakened in recent years, our findings also indicate the importance of continuous innovation in investing strategies.

**Table 1: Annualized decile portfolio returns**

This table shows the annualized arithmetic decile portfolio returns over the risk-free rate per investing formula. The decile portfolios are updated quarterly and returns are capped-value-weighted, with weights capped at the 80th percentile of the NYSE stocks market capitalization. Moreover, the table displays the annualized return spreads and CAPM alphas for the top-minus-bottom decile portfolios and the respective *t*-statistics. The sample period is July 1963 to December 2022.

| | **Piotroski F-Score** | **Magic Formula** | **Acquirer's Multiple** | **Conservative Formula** |
|---|---|---|---|---|
| | **Annualized excess returns ($R_p$ - $R_f$)** | | | |
| 1 (top) | 12.06% | 11.69% | 12.93% | 10.03% |
| 2 | 10.77% | 10.97% | 11.29% | 9.80% |
| 3 | 9.79% | 9.64% | 10.00% | 10.35% |
| 4 | 9.14% | 9.13% | 9.64% | 9.53% |
| 5 | 9.15% | 8.98% | 9.18% | 9.66% |
| 6 | 7.65% | 8.34% | 7.81% | 8.77% |
| 7 | 7.90% | 8.18% | 7.49% | 9.50% |
| 8 | 8.15% | 7.85% | 7.04% | 8.06% |
| 9 | 7.62% | 6.93% | 6.34% | 6.64% |
| 10 (bottom) | 6.43% | 5.88% | 7.04% | 3.59% |
| Top - Bottom | 5.63% | 5.82% | 5.89% | 6.44% |
| *t-statistics* | *(3.24)* | *(3.77)* | *(3.00)* | *(2.33)* |
| CAPM Alpha | 7.07% | 7.00% | 7.25% | 12.21% |
| *t-statistics* | *(4.15)* | *(4.60)* | *(3.73)* | *(5.41)* |

**Table 2: Factor analysis of the top-minus-bottom decile portfolios**

Panel A of this table shows the annualized arithmetic mean return and alphas for various factor models as well as the respective *t*-statistics for the top-minus-bottom decile portfolios. The decile portfolios are updated quarterly and returns are capped-value-weighted. Panel B shows the factor loadings for the Fama-French five-factor model plus momentum and its respective t-values. The sample period is July 1963 to December 2022.

| | **Piotroski F-Score** | **Magic Formula** | **Acquirer's Multiple** | **Conservative Formula** |
|---|---|---|---|---|
| | **Panel A: Alphas and t-values from asset pricing tests** | | | |
| Top - Bottom | 5.63% | 5.82% | 5.89% | 6.44% |
| | (3.24) | (3.77) | (3.00) | (2.33) |
| CAPM | 7.07% | 7.00% | 7.25% | 12.21% |
| | (4.15) | (4.60) | (3.73) | (5.41) |
| FF3FM | 3.61% | 6.27% | 4.32% | 14.16% |
| | (3.46) | (4.32) | (2.85) | (7.11) |
| FFC4FM | 1.79% | 7.77% | 5.33% | 3.00% |
| | (1.67) | (5.14) | (3.36) | (1.92) |
| FF5FM | 0.74% | 2.90% | 0.38% | 6.84% |
| | (0.76) | (2.45) | (0.31) | (3.90) |
| FF6FM | -0.09% | 4.15% | 1.42% | 0.23% |
| | -(0.09) | (3.46) | (1.13) | (0.16) |
| | **Panel B: Factors loading and t-values for the FF6FM** | | | |
| RMRF | -0.09x | -0.13x | -0.12x | -0.48x |
| | -(4.56) | -(5.46) | -(4.63) | -(16.50) |
| SMB | 0.12x | 0.03x | 0.13x | -0.62x |
| | (4.28) | (0.81) | (3.63) | -(15.42) |
| HML | 0.88x | 0.17x | 0.67x | 0.32x |
| | (23.04) | (3.57) | (13.90) | (5.76) |
| RMW | 0.44x | 0.94x | 1.00x | 0.58x |
| | (11.90) | (20.95) | (21.35) | (10.77) |
| CMA | 0.16x | -0.04x | 0.02x | 0.51x |
| | (3.05) | -(0.60) | (0.32) | (6.58) |
| MOM | 0.10x | -0.15x | -0.13x | 0.80x |
| | (3.65) | -(4.53) | -(3.61) | (19.87) |
| $R^2$ | 72.1% | 48.4% | 65.2% | 76.7% |

**Table 3: Performance summary statistics for concentrated long-only portfolios**

This table shows the performance summary statistics for concentrated long-only portfolios of the 40 top-ranked stocks per investing formula. The metrics are geometric return, standard deviation, Sharpe ratio (using arithmetic returns), maximum drawdown, tracking error, information ratio as well as CAPM beta and alpha. All performance metrics are annualized, with the exception of maximum drawdown and CAPM beta. Panel A shows the statistics for capped-value-weighted portfolios, with weights capped at the 80$^{th}$ percentile of the NYSE stocks market capitalization, while Panel B shows equally-weighted portfolios. The portfolios are updated quarterly, and the sample period is from January 2000 to December 2022.

| | Annual Return | Std. Deviation | Sharpe Ratio | Max. Drawdown | Tracking Error | Information Ratio | CAPM Beta | CAPM Alpha |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Value-weighted** | | | | | | | | |
| **Piotroski F-Score** | 13.2% | 23.1% | 0.59 | 57.5% | 14.4% | 0.49 | 1.19 | 5.8% |
| **Magic Formula** | 15.8% | 22.7% | 0.69 | 50.6% | 13.6% | 0.67 | 1.20 | 7.8% |
| **Acquirer's Multiple** | 14.2% | 26.9% | 0.57 | 53.6% | 17.0% | 0.52 | 1.41 | 6.0% |
| **Conservative Formula** | 11.4% | 13.0% | 0.78 | 40.1% | 9.7% | 0.36 | 0.66 | 5.8% |
| **Market** | 7.2% | 15.3% | 0.43 | 44.1% | - | - | 1 | - |
| **Panel B: Equally weighted** | | | | | | | | |
| **Piotroski F-Score** | 14.0% | 23.7% | 0.61 | 57.4% | 10.3% | 0.30 | 1.15 | 1.3% |
| **Magic Formula** | 16.9% | 22.4% | 0.75 | 49.6% | 9.1% | 0.58 | 1.10 | 4.1% |
| **Acquirer's Multiple** | 17.0% | 27.4% | 0.66 | 52.2% | 12.4% | 0.53 | 1.35 | 2.5% |
| **Conservative Formula** | 11.5% | 12.9% | 0.80 | 39.6% | 11.5% | -0.10 | 0.55 | 4.0% |
| **Market** | 11.8% | 18.7% | 0.61 | 47.3% | - | - | - | - |

**Table 4: Annual returns for concentrated long-only portfolios**

This table shows annual returns for concentrated long-only portfolios of the 40 top-ranked stocks per investing formula. The portfolios are updated quarterly and returns are capped-value-weighted, with weights capped at the 80th percentile of the NYSE stocks market capitalization. The Market returns are the value-weighted returns of all stocks in our final stock universe. The sample period is January 2000 to December 2022.

| | Piotroski F-Score | Magic Formula | Acquirer's Multiple | Conservative Formula | Market |
|---|---|---|---|---|---|
| 2000 | 24.2% | 20.3% | 23.2% | 22.9% | -8.9% |
| 2001 | 20.1% | 66.3% | 49.8% | 14.9% | -8.2% |
| 2002 | -2.9% | 2.0% | -9.7% | 4.4% | -22.9% |
| 2003 | 44.8% | 48.2% | 49.7% | 16.4% | 25.8% |
| 2004 | 17.9% | 31.8% | 27.8% | 14.8% | 10.4% |
| 2005 | 17.9% | 4.3% | 13.9% | 11.5% | 6.1% |
| 2006 | 22.2% | 17.5% | 17.5% | 13.1% | 13.0% |
| 2007 | 6.0% | 2.6% | -2.7% | 3.5% | 11.9% |
| 2008 | -36.4% | -41.4% | -36.1% | -29.7% | -34.8% |
| 2009 | 64.9% | 55.5% | 70.9% | 12.8% | 27.5% |
| 2010 | 18.2% | 18.8% | 22.7% | 19.7% | 17.4% |
| 2011 | 8.5% | 7.6% | 1.9% | 12.4% | 5.5% |
| 2012 | 28.1% | 8.7% | 10.4% | 13.1% | 13.6% |
| 2013 | 33.3% | 47.5% | 39.1% | 31.9% | 28.4% |
| 2014 | 11.1% | 9.4% | 3.8% | 15.3% | 12.0% |
| 2015 | -9.8% | -5.2% | -15.2% | 9.8% | 1.4% |
| 2016 | 29.9% | 18.5% | 35.3% | 11.4% | 12.1% |
| 2017 | 12.5% | 13.3% | 13.2% | 23.1% | 19.9% |
| 2018 | -24.9% | -9.1% | -15.5% | -3.8% | -2.3% |
| 2019 | 13.3% | 29.0% | 25.7% | 22.3% | 28.9% |
| 2020 | 19.9% | 24.4% | 29.8% | 7.7% | 26.8% |
| 2021 | 32.9% | 26.6% | 32.0% | 19.9% | 22.4% |
| 2022 | -2.6% | 0.0% | 1.6% | 0.3% | -18.7% |
| **Average** | **15.2%** | **17.2%** | **16.9%** | **11.7%** | **8.1%** |

**Figure 1: Cumulative relative performance of the top and the bottom deciles**

This figure shows the cumulative compounded performance of the top and bottom deciles divided by the cumulative compounded performance of the market per investing formula. The decile portfolios are updated quarterly and capped-value-weighted decile portfolios, with weights capped at the 80th percentile of the NYSE stocks market capitalization. The market is the value-weighted return of all stocks in our final sample. The sample period is July 1963 to December 2022.

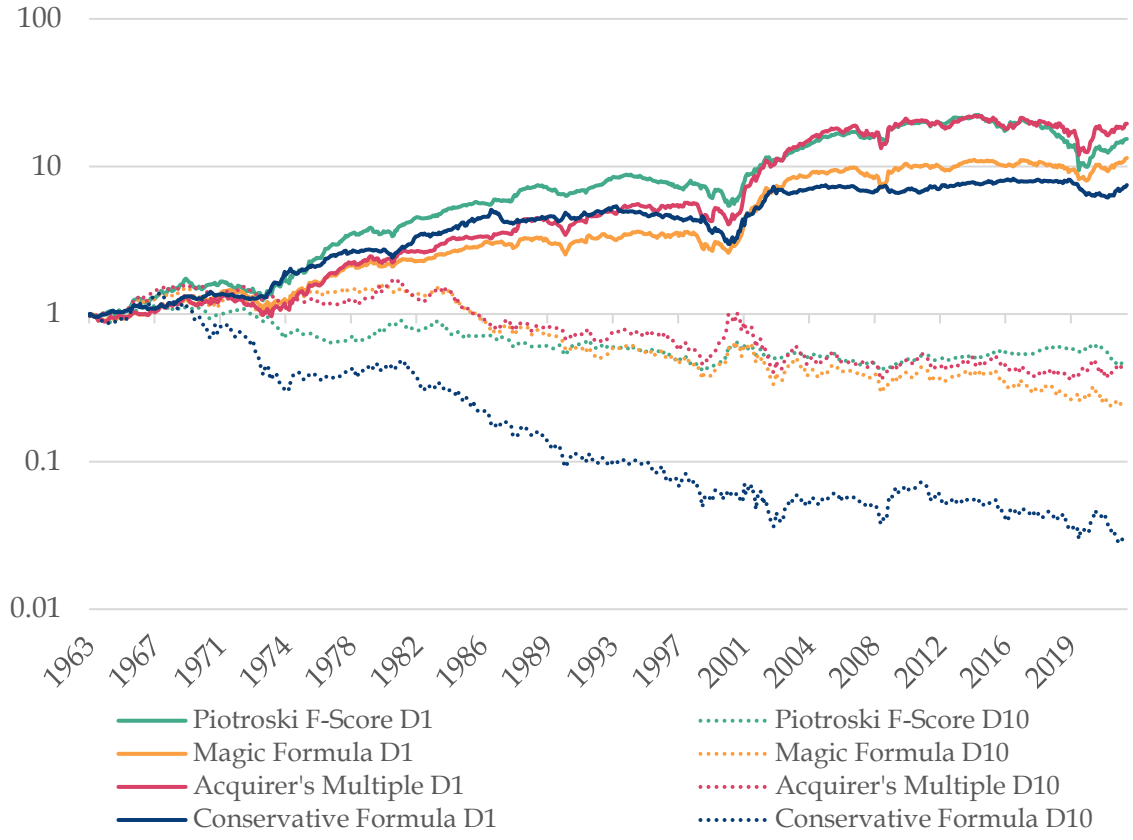
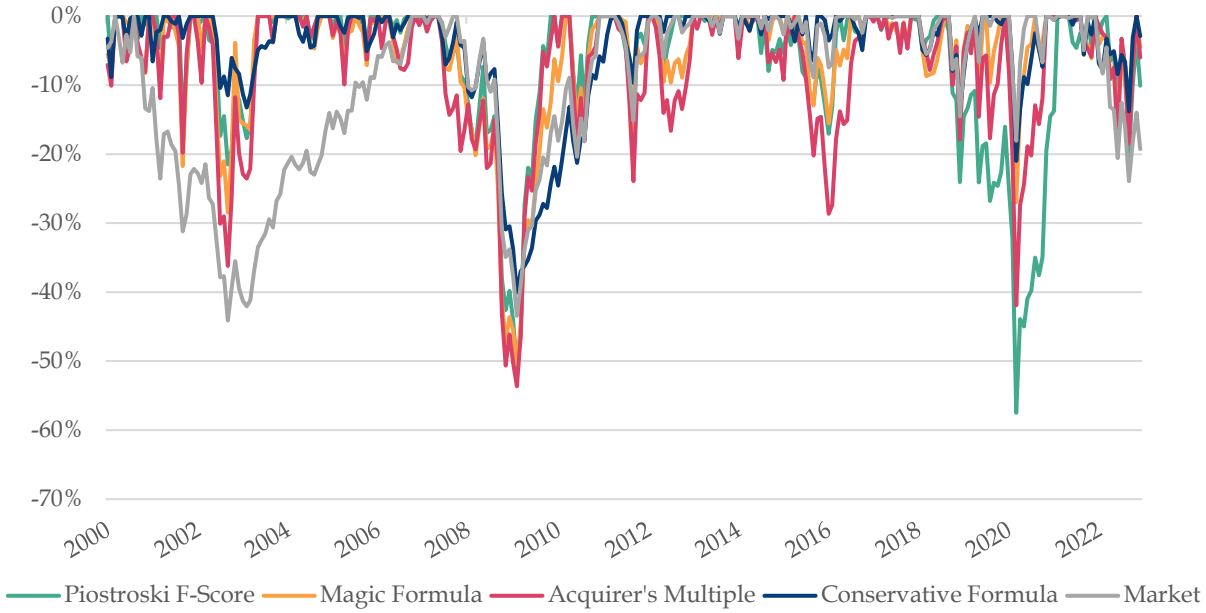


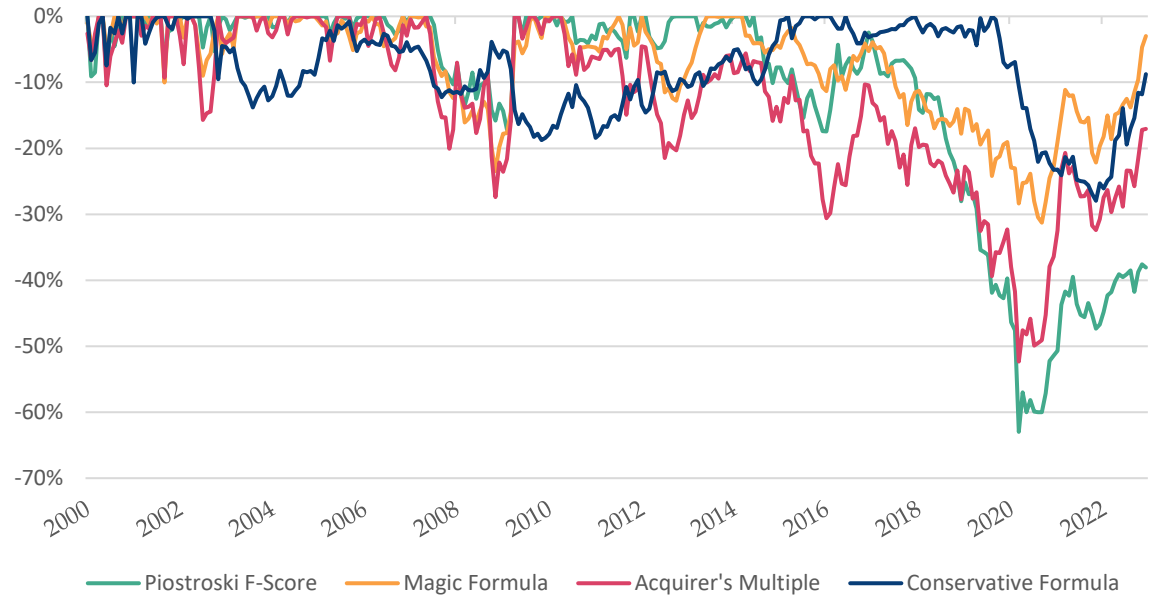
**Figure 2: Absolute and relative drawdowns**

This figure shows the absolute (Panel A) and relative (Panel B) drawdowns for concentrated long-only portfolios of the 40 top-ranked stocks per investing formula. The portfolios are updated quarterly and returns are capped-value-weighted, with weights capped at the 80th percentile of the NYSE stocks market capitalization. The market is the value-weighted return of all stocks in our final sample. The sample period is January 2000 to December 2022.

**Panel A**




**Panel B**



**Appendix**

**A1 Additional formula details**

Invested Capital:

$$IC = \max\{\,(\,COWC + NCOFA\,);\ 1\,\}$$

With:

(1) $$\begin{gathered} Current\ Operating\ Working\ Capital\ (COWC) = \\ Current\ Assets\ (item\ CA) - \\ Cash\ \&\ Equivalents\ (item\ CHE) - \\ Current\ Liabilities\ (item\ CL) + \\ Interest\ Bearing\ Current\ Liabilities\ (item\ DLC) \end{gathered}$$

(2) $$\begin{gathered} Non - Current\ Opertaing\ Fixed\ Assets\ (NCOFA) = \\ Total\ Assets\ (item\ AT) - \\ Current\ Assets\ (item\ CA) - \\ Investments\ \&\ Advances\ (item\ IV) - \\ Intangible\ Assets\ (item\ INTAN) \end{gathered}$$

Enterprise Value:

$$EV = \max\{\,(\,MC + PS + MI + ND\,);\ 1\,\}$$

With:

(1) MC being the market capitalization at portfolio formation.

(2) PS being the value of preferred stock (item PSTKRV)

(3) MI being minority interest (item MIB)

(4) ND being the net debt:

Net Debt:

$$\begin{gathered} ND = \\ short\ term\ debt\ (item\ DLC) + \\ long\ term\ debt\ (item\ DLTT) - \\ cash\ \&\ equivalents\ (item\ CHE) \end{gathered}$$

**Table A1: Compustat Data Items**

This table describes the different data items used from Compustat and their description. Furthermore, it shows how data items were calculated if the original data item is not available to maximize the amount of sample data. The first column describes the accounting item, while the second column includes its symbol. Columns 3 to 5 show in order which Compustat items were used for this accounting item. It can be understood in the sense that when the "First Choice" is not available, the second choice will be used, and so on. If a name ends with the tailpiece "_x," it is a preprocessed Compustat item; otherwise, the codes are the direct Compustat item codes. If a code has the prefix "lag_" it refers to the respective item as of year t-1. Items that are in brackets in the form of "(xyz,0)" mean that if the first item ("xyz") is not available, the second item will be used ("0"). The item process and hence the table follow the code (available on their GitHub) of Jensen et al. (2023b).

| Item Description | Short Name | First Choice | Second Choice | Third Choice |
|---|---|---|---|---|
| Book Equity | be_x | seq_x + (txc,0) - (pstk_x,0) | | |
| Common Equity Issuance | scstkc_x | scstkc_x | eqis_x | |
| Current Assets | ca_x | act | rect + invt + che + aco | |
| Current Liabilities | cl_x | lct | ap + dlc + txp + lco | |
| Current Operating Working Capital | cowc_x | coa_x - col_x | | |
| Debt | debt_x | dltt + dlc | | |
| Deferred Tax Credit | txc_c | txditc | txdb | itcb |
| Equity Issuance | eqis_x | sstk | | |
| Gross Profit | gp_x | gp | sale_x - cogs | |
| Minority Interest | mib_x | (mib,0) | | |
| Net Income ex. unusual items | ni_x | ib | ni | |
| Net Non-Current Operating Assets | nncoa_x | ncoa_x - ncol_x | | |
| Netdebt | netdebt_x | debt_x - (che,0) | | |
| Non-Current Debt | dltt | dltt | | |

| Item Description | Short Name | First Choice | Second Choice | Third Choice |
|---|---|---|---|---|
| Non-Current Operating Assets | ncoa_x | at_x - ca_x - (ivao,0) | | |
| Non-Current Operating Fixed Assets | ncofa_x | ncoa_x - (intan, 0) | | |
| Non-Current Operating Liabilities | ncol_x | lt - cl_x - dltt | | |
| Operating Accruals | oacc_x | ni_x - oancf | cowc_x - lag_cowc_x + nncoa_x - lag_nncoa_x | |
| Operating Cash Flow | ocf_x | oancf | ni_x - oacc_x | ni_x + dp - (wcapc,0) |
| Operating Current Assets | coa_x | ca_x - che | | |
| Operating Current Liabilities | col_x | cl_x - (dlc, 0) | | |
| Operating Earnings Before Interest & Taxes | ebit_x | ebit | oiadp | ebitda_x - dp |
| Operating Earnings Before Interest, Taxes and Depreciation & Amortization | ebitda_x | ebitda | oibdp | sale_x - opex_x |
| Operating Expenses | opex_x | xopr | cogs + xsga | |
| Revenue | sale_x | sale | revt | |
| Shareholders' Equity | seq_x | seq | ceq + (pstk_x, 0) | at - lt |
| Total Assets | at_x | at | seq_x + dltt + (lct, 0) | |
| Value of Preferred Stock | pstk_x | pstkrv | pstkl | pstk |

**Table A2: Detailed decile portfolio performance statistics**

This table shows detailed decile performance statistics for each investing formula. The performance statistics are average arithmetic total return, standard deviation, Sharpe ratio, CAPM beta, CAPM alpha, and the associated *t*-statistic. All performance metrics are annualized, with the exception of the CAPM beta. The decile portfolios are updated quarterly and capped-value-weighted, with weights capped at the 80th percentile of the NYSE stocks market capitalization. The sample period is July 1963 to December 2022.

| **Panel A: F-Score** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 1-10 |
| Average Return | 16.4% | 15.1% | 14.1% | 13.5% | 13.5% | 12.0% | 12.2% | 12.5% | 12.0% | 10.8% | 5.6% |
| Std. Deviation | 18.4% | 17.5% | 17.2% | 16.8% | 17.7% | 17.5% | 17.7% | 17.6% | 18.0% | 19.8% | 13.4% |
| Sharpe Ratio | 0.66 | 0.61 | 0.57 | 0.54 | 0.51 | 0.44 | 0.44 | 0.46 | 0.42 | 0.32 | 0.42 |
| Beta | 1.02 | 1.03 | 1.03 | 1.02 | 1.08 | 1.09 | 1.11 | 1.11 | 1.13 | 1.23 | -0.21 |
| Alpha | 5.1% | 3.7% | 2.7% | 2.1% | 1.7% | 0.1% | 0.3% | 0.5% | -0.1% | -2.0% | 7.1% |
| *t-statistic* | *3.79* | *3.37* | *2.74* | *2.27* | *1.81* | *0.17* | *0.33* | *0.67* | *-0.15* | *-2.03* | *4.15* |
| **Panel B: Magic Formula** | | | | | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 1-10 |
| Average Return | 16.0% | 15.3% | 14.0% | 13.5% | 13.3% | 12.7% | 12.5% | 12.2% | 11.3% | 10.2% | 5.8% |
| Std. Deviation | 19.1% | 17.9% | 17.4% | 17.2% | 17.1% | 16.9% | 16.8% | 16.9% | 17.3% | 22.4% | 11.9% |
| Sharpe Ratio | 0.61 | 0.61 | 0.55 | 0.53 | 0.52 | 0.49 | 0.49 | 0.46 | 0.40 | 0.26 | 0.49 |
| Beta | 1.12 | 1.07 | 1.06 | 1.07 | 1.08 | 1.07 | 1.05 | 1.04 | 1.05 | 1.29 | -0.17 |
| Alpha | 4.0% | 3.6% | 2.4% | 1.8% | 1.5% | 1.0% | 1.0% | 0.7% | -0.3% | -3.0% | 7.0% |
| *t-statistic* | *3.34* | *3.47* | *2.47* | *2.14* | *2.11* | *1.36* | *1.24* | *0.80* | *-0.26* | *-2.00* | *4.60* |
| **Panel C: Acquirer's Multiple** | | | | | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 1-10 |
| Average Return | 17.3% | 15.6% | 14.3% | 14.0% | 13.5% | 12.2% | 11.8% | 11.4% | 10.7% | 11.4% | 5.9% |
| Std. Deviation | 20.7% | 18.3% | 17.4% | 17.1% | 16.3% | 16.3% | 16.4% | 17.3% | 19.0% | 23.3% | 15.1% |
| Sharpe Ratio | 0.62 | 0.62 | 0.57 | 0.56 | 0.56 | 0.48 | 0.46 | 0.41 | 0.33 | 0.30 | 0.39 |
| Beta | 1.16 | 1.06 | 1.03 | 1.03 | 0.99 | 1.01 | 1.02 | 1.09 | 1.17 | 1.35 | -0.20 |
| Alpha | 5.0% | 4.0% | 2.9% | 2.6% | 2.4% | 0.9% | 0.5% | -0.5% | -1.7% | -2.3% | 7.2% |
| *t-statistic* | *3.32* | *3.33* | *2.73* | *2.67* | *2.66* | *1.08* | *0.60* | *-0.61* | *-1.76* | *-1.48* | *3.73* |
| **Panel D: Conservative Formula** | | | | | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 1-10 |
| Average Return | 14.4% | 14.1% | 14.7% | 13.9% | 14.0% | 13.1% | 13.8% | 12.4% | 11.0% | 7.9% | 6.4% |
| Std. Deviation | 13.1% | 13.9% | 14.9% | 15.7% | 16.8% | 18.0% | 19.6% | 21.5% | 23.1% | 27.8% | 21.4% |
| Sharpe Ratio | 0.76 | 0.71 | 0.69 | 0.61 | 0.57 | 0.49 | 0.48 | 0.37 | 0.29 | 0.13 | 0.30 |
| Beta | 0.74 | 0.84 | 0.91 | 0.97 | 1.05 | 1.12 | 1.21 | 1.31 | 1.38 | 1.58 | -0.84 |
| Alpha | 5.0% | 4.0% | 4.1% | 2.9% | 2.5% | 1.1% | 1.2% | -0.9% | -2.8% | -7.3% | 12.2% |
| *t-statistic* | *5.38* | *5.25* | *5.31* | *3.63* | *3.08* | *1.26* | *1.19* | *-0.78* | *-2.03* | *-3.78* | *5.41* |

**Table A3: Annualized equal-weighted decile portfolio returns**

This table shows the annualized arithmetic decile portfolio returns over the risk-free rate per investing formula. The decile portfolios are updated quarterly and returns are equally weighted. Moreover, the table displays the annualized return spreads and CAPM alphas for the top-minus-bottom decile portfolios and the respective *t*-statistics. The sample period is July 1963 to December 2022.

| | **Piotroski F-Score** | **Magic Formula** | **Acquirer's Multiple** | **Conservative Formula** |
|---|---|---|---|---|
| | **Annualized excess returns ($R_p$ - $R_f$)** | | | |
| 1 (top) | 12.41% | 12.10% | 13.37% | 10.25% |
| 2 | 11.69% | 11.50% | 11.64% | 10.33% |
| 3 | 10.50% | 10.23% | 10.45% | 10.66% |
| 4 | 9.67% | 9.41% | 9.96% | 10.01% |
| 5 | 9.52% | 9.42% | 9.59% | 10.33% |
| 6 | 7.97% | 8.78% | 8.04% | 9.23% |
| 7 | 8.07% | 8.52% | 7.90% | 9.94% |
| 8 | 8.50% | 8.24% | 7.55% | 8.89% |
| 9 | 7.72% | 7.65% | 6.49% | 7.62% |
| 10 (bottom) | 6.33% | 6.48% | 7.32% | 5.09% |
| Top - Bottom | 6.08% | 5.62% | 6.04% | 5.16% |
| *t-statistics* | *(3.52)* | *(3.80)* | *(3.28)* | *(1.86)* |
| CAPM Alpha | 7.42% | 6.95% | 7.49% | 11.03% |
| *t-statistics* | *(4.37)* | *(4.82)* | *(4.13)* | *(4.93)* |

**Figure A1: Cumulative performance of the top vs. the bottom deciles**

This figure shows the cumulative compounded performance of the top decile divided by the cumulative compounded performance of the bottom decile per investing formula. The decile portfolios are updated quarterly, and returns are capped-value-weighted, with weights capped at the 80th percentile of the NYSE stocks market capitalization. The sample period is July 1963 to December 2022.

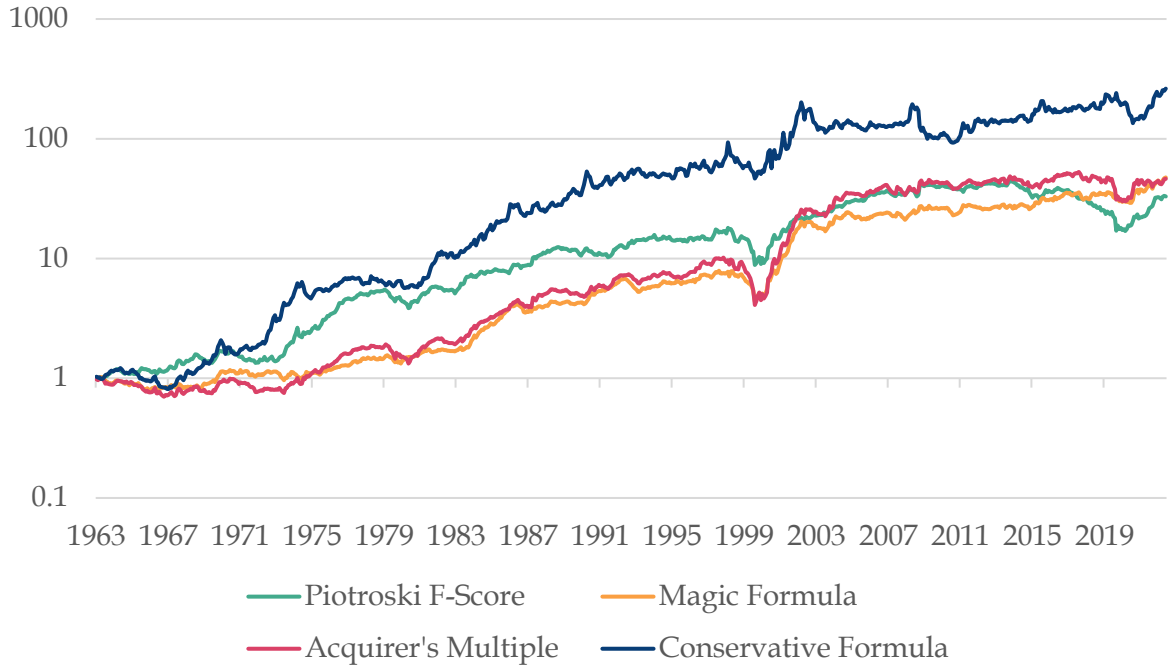
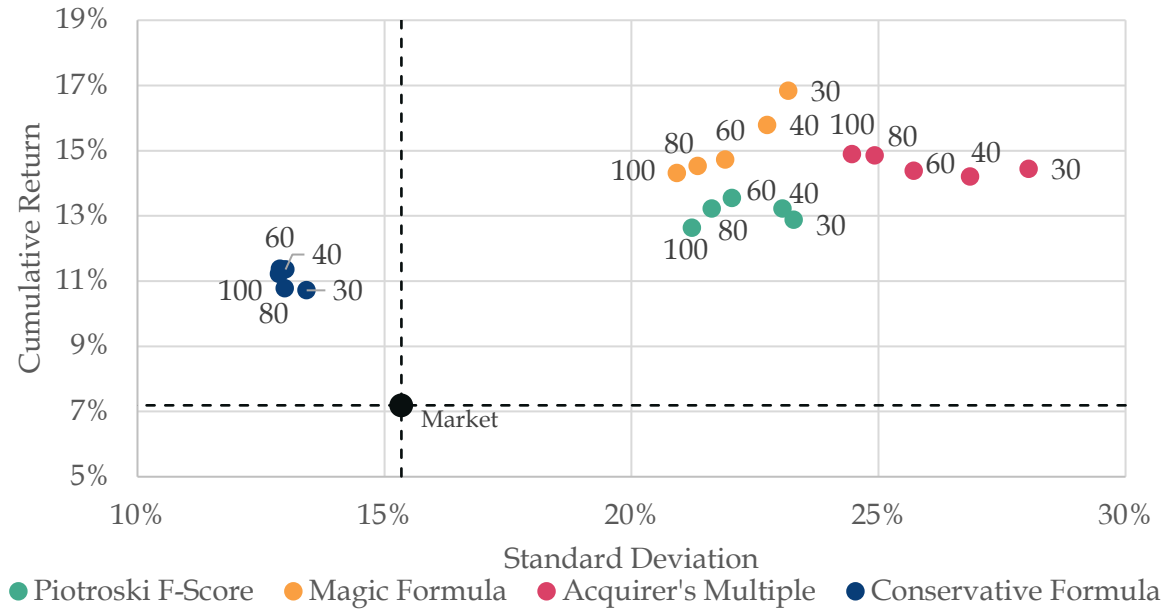


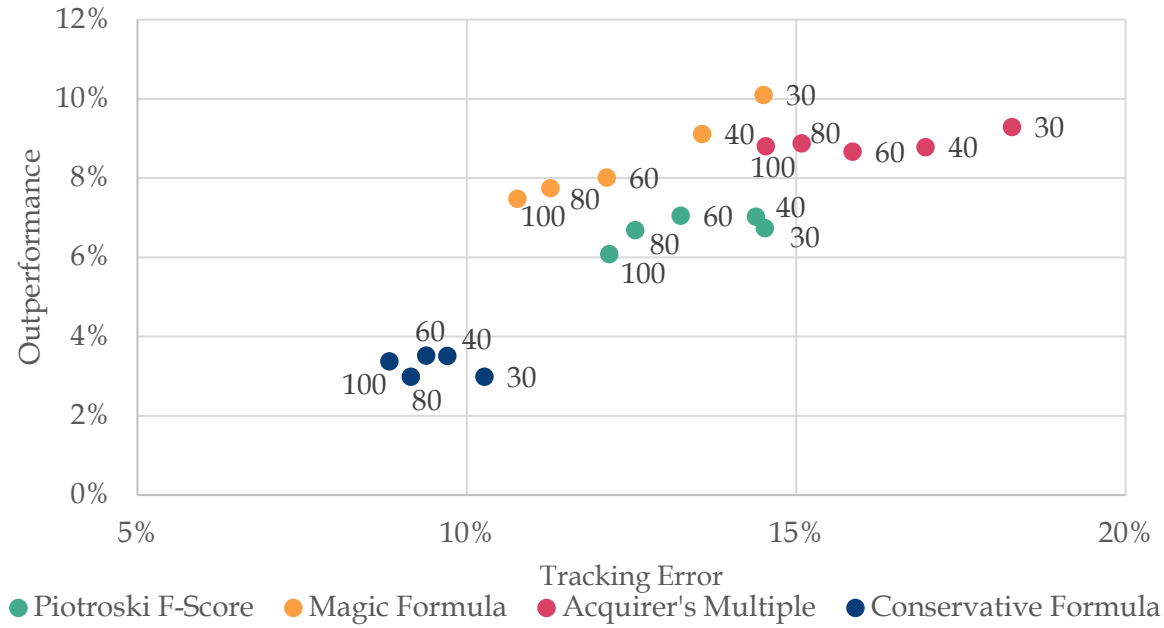
**Figure A2: Risk-return per formula and portfolio size**

These two figures show the annualized performance of concentrated long-only portfolios with different numbers of stocks for each formula. The portfolios are updated quarterly and capped-value-weighted, with weights capped at the 80th percentile of the NYSE stocks market capitalization. Panel A (B) takes an absolute (relative) return perspective and shows the standard deviation (tracking error) on the x-axis and the Cumulative return (outperformance) on the y-axis. The market is the value-weighted return of all stocks in our final sample. The sample period is January 2000 to December 2022.

**Panel A**




**Panel B**



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