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RESEARCH ARTICLE

Tailor-made strategies through different weight simulation of factor-based investing

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Abstract

This study explores the implementation and factor integration of diverse factor-based investment strategies in the European market. Specifically, we investigate a contrarian strategy, two value strategies, and a momentum strategy from 2015 to June 2024. Utilising the Python framework Qrumble for efficient experimentation, we integrate evaluation metrics and we consider beyond the commonly used portfolios, equally weighted and value-weighted, two theoretically efficient portfolios - minimum variance and market portfolio. While certain strategies yielded outcomes not entirely in line with state-of-the-art standards, both value strategies showed promising returns with manageable risk. Notably, the combination of factors in a multi-type strategy, named Magical Bambu, demonstrated interesting results, suggesting the potential for effective collaboration between different investment methodologies. This study underscores the nuanced outcomes within theoretically efficient portfolios under specific conditions, prompting further exploration.

Keywords Factor-based investing · Efficient portfolio · Computational simulation

JEL Classification G11 · G40

1 Introduction

In the constantly changing world of investments, the pursuit of personalized and effective strategies is of great significance. This paper analyses empirical experiments, comparing various investment strategies, from classic approaches to testing of diverse strategies, leading to an adapted one. Our objectives are threefold: (1) To compare

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a range of classic and adapted investment strategies, aiming to identify those that best meet investors' needs. (2) To acknowledge that different strategies may be better suited for different types of investors, taking into account their goals, risk tolerance, and investment horizon. (3) To highlight distinct features in investments by comparing strategies with various portfolio weighting schemes. Recent studies, such as Ljungberg and Högstedt (2021), have shown that combining traditional strategies like the Magic Formula with modern portfolio theory can lead to improved risk-adjusted returns.

This study provides empirical evidence that integrating multiple factors, such as momentum, value, and quality, can improve risk-adjusted performance in the European market, as supported by recent research (Siirtola 2021). Our contribution to the field of investments includes the introduction and empirical evaluation of a new multi-factor strategy called Magical Bambu (Sect. 2.6). Additionally, we examine the limitations of the Capital Asset Pricing Model (CAPM), portfolio return variability, and equal weighting, particularly for diverse portfolios. By simulating investments with tailored factor adjustments, we present how customized strategies can align more closely with individual investor profiles and objectives. Our results suggest that combining fundamental and technical factors can enhance portfolio performance. This paper offers insights into the potential of various weighting schemes for developing factor-based strategies, providing empirical support for their effectiveness.

This study is grounded in factor-based investing, which originated from within the industry's practitioners and has received extensive academic attention. Markowitz (1952) found that the security analysis by Graham and Dodd (1934) was too focused on maximising the portfolio's expected returns, that it ignored the high risks associated with it. In response to this, Markowitz (1952) treated the income streams by distribution moments and brought the concept of portfolio diversification, by diminishing the variability of portfolio returns to a point of being arbitrarily small, over a sufficiently large number of independent risks. Accordingly, there was a way to discover efficient portfolios that would satisfy risk-averse investors, by finding the portfolio with the lowest possible variance for a given expected return. Influenced by the previous work, Treynor (1961), Sharpe (1964), Lintner (1975) and Mossin (1966) were determined in reaching the equilibrium of financial markets with the CAPM, assuming that all investors have mean-variance preferences. The CAPM also proposed that portfolio returns depend on market reward and its co-movement with the market. In contrast, Ross (1976) introduced the Arbitrage Pricing Theory (APT), which considers multiple forms of systematic risk, though it does not specify which risks justify compensation. In APT, an asset's expected return is modelled as a function of various macroeconomic factors or theoretical market indexes (Bender et al. 2013). With the popularisation of the term factor, the APT turned out to be the basis of multi factor-based investing (Bender et al. 2013). Even though the CAPM supplied the theoretical framework for pricing investments, the empirical data and supposed anomalies sometimes seems to contradict this theory, e.g. influential stock characteristics in (Basu 1977) or the higher risk of small market capitalisation in Banz (1981), (see (Pappas and Dickson 2015)). The general accepted idea that came with the Efficient Market Hypothesis (Fama 1970), was that news and information were quickly translated into security prices and markets were efficient by nature. Therefore, there was no need or motivation to apply fundamental analysis (study of public information and financial statements) nor technical analysis (study of past stock prices to predict future ones) to generate higher returns. However, that was contested with rationale and criticism by proposers of value investing, contrarian investing and momentum. Research by Domingues et al. (2022) has further challenged this notion by demonstrating that value investing strategies can generate positive and statistically significant Jensen's alpha, even in multifactor model settings.

Value investing, first created by Graham and Dodd (1934), is an approach to help with the allocation of capital based on fundamental factors. This originated with the idea of comparing an asset's price with its intrinsic value, since the former is a volatile measure of a company's valuation and not always equal to its true market value. This fluctuation is the baseline of finding and investing in undervalued businesses, i.e., when the share price is lower than its intrinsic value, with the hope that its price value will rise to its true worth in the future. The authors possessed an entrepreneurial school of thought, in a way that crafting an investment revolved around the principles of the business economy would lead to more success. In this strategy, they prioritized fundamental factors such as low debt-to-equity ratio and high dividend yields. Fama and French (1992) were inspired by the classification of value companies and found that firms with low market capitalisation and a lower price to book value have better returns than the contrary. In the midst of understanding the origin of premium value, they associated it as a risk compensation hypothesis. The three-factor model (Fama and French 1993) is then created with market excess return, book-to-market factor (high-minus-low book-to-market) and company size effect (small-minus-big). This expansion of the CAPM with size risk and value risk factors showcased promising results. There is a comparable investment strategy that resembles value investing, called contrarian investment strategy, but takes into consideration the psychological reasoning of the market's behaviour. Contrarians recognise unpopular, financially distressed companies and try to buy them for cheap, with the expectation that they will later rebound.

Contrarian strategies were first created by De Bondt and Thaler (1985) and are rooted on the overreaction hypothesis, where investors react excessively to information, increasing stock price oscillations. If the oscillation turned out to be positive, then investors would be overly optimistic, leading to overpriced assets, while the opposite would occur alongside with excessive pessimism if price movements were negative. This phenomenon was later associated with representativeness bias (Barberis et al. 1998), where businesses with good results are viewed as a representative of a good business, which investors will trust their capital on the most. This induces extreme mispricing and overconfidence. Although value and contrarian investing are analogous, the first one focuses on value ratios while the second can also analyse past returns to help in identifying loser and winner stocks. Interestingly, Jagirdar and Gupta (2023) has shown that value and contrarian investment strategies, despite their similarities, often select different stocks at any given point in time, challenging the assumption that these strategies pick the same stocks.

Besides this, there was a completely divergent perspective submerging, with the intention of comprehending investors' reaction to new information and profiting from higher returns. In the 70's, financial researchers were certain that stock prices followed a random walk and patterns were just the consequence of data snooping, so past information couldn't estimate future stock prices (Fama 1970). As in the paragraph above, this faced a lot of criticism from anomalies not only by value investing enthusiasts, but also by momentum investing researchers. Although Levy (1967) introduced the momentum term of "relative strength" first, momentum investing gained its popularity by Jegadeesh and Titman (1993), when they demonstrate that equities with higher past returns persist on having superior returns in the future, over the next three to twelve months, and equities with lower past returns tend to worsen their future returns within the next months. Thus, buying the past winners and selling the past losers would generate substantial profits. Momentum strategies were then based on the underreaction hypothesis, in the sense that investors don't react much to new information and asset prices fall short on adapting adequately. This strategy of investing relies on short-term analysis and short-term profit for success.

The question whether momentum and value investing could benefit from one another remained, and there were some research studies that reported momentum payoffs alongside fundamentals. Asem (2009) argued for enhanced momentum payoffs in taking long positions in stocks that had raised dividends and short on assets that had done the opposite, with the underreaction hypothesis in mind. Booth et al. (2016) revealed momentum effect alongside with firm size, where "small-firm effect dominates price momentum in the long run", in support of rational theory.

2 Factor-based investment strategies

This section introduces the need for ranking companies by briefly presenting four classic factor-based investment strategies underlying our experiences. The Dogs of the Dow (DoD), developed in 1991, targets volatility within the Dow Jones Industrial Average (O'Higgins and Downes 2011). The Magic Formula (MF), published in 2006, identifies undervalued companies based on capital efficiency and earnings (Greenblatt 2006). The "Buying Winners and Selling Losers" (WL) strategy, proposed in 1993, focuses on high-return businesses by Jegadeesh and Titman (1993). Lastly, the F-Score method by Piotroski, introduced in 2000, evaluates companies' historical data to identify undervalued firms with strong returns (Piotroski 2000).

2.1 Ranking formula

All four investment strategies presented previously are purely quantitative and rank stocks based on one or more factors as part of their stock selection processes. The first two strategies involve buying the top-ranked stocks and holding them in an equal-weight, long-only portfolio for one year. The other two strategies involve buying the top-ranked stocks and simultaneously selling the bottom-ranked stocks into an equal-weight, long-short portfolio (Chincarini and Kim 2006). These portfolios are held for six months and one year respectively. After the holding period, all strategies repeat the exact same stock-selection process. A new long-only (long-short) portfolio is formed with the newly selected stocks and these stocks are held again for the same amount of time. Any gains made between portfolios are reinvested.

To formalise the stock selection process for all factor-based investing strategies, including both classic and tailor-made, the following ranking formula is introduced:

$$score_{b/r} = F_1^{\langle +/- \rangle} + F_2^{\langle +/- \rangle} + \ldots + F_k^{\langle +/- \rangle}. \tag{1}$$

It relies on a set of factors denoted as $F_1, F_2, \ldots, F_k$, representing fundamental or technical indicators about companies. Factor loadings are fixed to 1. Factors may vary in number depending on the specific investment strategy. Before being combined to produce a score, all factors are scaled to the same range. Scaling can be separately performed in either ascending order, denoted $F_i^{\langle + \rangle}$, or descending order, denoted $F_i^{\langle - \rangle}$, for any factor F_i in (1), so to determine the relative importance of the factor values compared to other stocks and factors, depending on the investment strategy. This scaling process ensures that the formula remains unbiased towards high-magnitude indicators. Each stock under analysis (stock universe) is assigned a score, based on which they are subsequently ranked. The investment strategy then selects the top-ranked stocks for buying and the bottom-ranked stocks for selling, if short-selling is involved.

The scaling methods used are *binary scaling* $\{0, 1\}$ or *rank scaling* $\{1, \ldots, U\}$, with U representing the size of the stock universe. Binary scaling maps factor values to 1 if positive (negative) and in ascending (descending) order. Conversely, it maps factor values to 0 if positive (negative) and in descending (ascending) order. In simpler terms, if a stock has a positive (or negative) factor value that is a proponent of a good investment, it is mapped to 1, otherwise to 0. Rank scaling ranks values either in ascending or descending order, for each factor separately. This ranking is used to map a factor value to its corresponding position in the rank. As a result, each factor value uniquely maps to a value in the range $\{1, \ldots, U\}$, where U is the size of the stock universe. In ascending order, the highest factor value is mapped to U, while the lowest is mapped to 1. This mapping is reversed for descending order.

When all factors are binary scaled, (1) yields a score per stock, denoted by $score_b$, within the integer range $\{0, \ldots, k\}$. When all factors are rank scaled, (1) yields a score per stock, denoted by $score_r$, within the integer range $\{k, \ldots, kU\}$, with U the size of the universe. In both cases, the lower boundary limit means the worst possible score, while the upper boundary limit means the best possible score a stock can potentially have.

2.2 European Dogs of the Dow

This investment strategy is taken from O'Higgins and Downes (2011) and adapted to the European market. Instead of using the Dow Jones as in the original strategy, the stock universe in this case is the largest 30 companies of the STOXX 600 by market cap. The corresponding ranking formula is:

$$score_r = \text{Yield}^{\langle + \rangle}. \tag{2}$$

This strategy uses rank scaling, according to Sect. 2.1. The biggest 30 companies of the STOXX Europe 600 are ranked by Yield in ascending order, with the top 10 invested for one year. Yield is the percentage of total dividends in one year relative to the stock price, per share.

2.3 European Magic Formula

This investment strategy is taken from Greenblatt (2006), with slight adaptations for the European market. Instead of using the 3,500 largest US stocks, we chose the STOXX Europe 600 as the stock universe. From the STOXX 600, the strategy excludes stocks from both the financial and utility sectors. It is from this final universe that the ranking formula is applied for stock selection, which in this case takes the form:

$$score_r = \text{Earnings Yield}^{\langle + \rangle} + \text{ROC}^{\langle + \rangle}. \tag{3}$$

Stocks from the STOXX 600, excluding financials and utilities, are ranked by Earnings Yield and by ROC in ascending order, and these two ranks are added together to produce a final score, per stock. The resulting top 30 stocks are invested for one year. Earnings Yield is the percentage of earnings in one year relative to the market price and ROC is the return-on-capital, which is one-year EBIT (earnings before interest and taxes) divided by the capital employed into the business (Greenblatt 2006).

2.4 European Buying Winners and Selling Losers

This investment strategy is taken from Jegadeesh and Titman (1993) and adapted to the STOXX 600 universe. Once again, the STOXX 600 is chosen as the stock universe in place of the NYSE and AMEX Composite Indexes of the original strategy. The ranking formula is:

$$score_r = \text{RS 6m}^{\langle + \rangle}. \tag{4}$$

Stocks from the STOXX 600 are ranked by RS 6 m in ascending order. RS 6 m is the relative (price) strength in the trailing 6-month window, which is a measure of how the stock price went up (or down) within the past 6 months, relative to the market. Stocks in the top 10% are bought while stocks in the bottom 10% are shorted, for 6 months.

2.5 European F-Score

This investment strategy is taken from Piotroski (2000), but with slight adaptations due to our European sample. The stock universe is again the STOXX 600. From this, the strategy redefines the universe by only considering the top quintile B/M (book-to-market) stocks. To do so, all STOXX 600 constituents are sorted by B/M and only the top 20% are considered. From this final universe the corresponding ranking formula is applied for stock selection, which is:

$$\begin{aligned} score_b =& \mathrm{ROA}^{\langle + \rangle} + \mathrm{OCF}^{\langle + \rangle} + \Delta\mathrm{ROA}^{\langle + \rangle} + \text{Accrual Ratio}^{\langle - \rangle} \\ &+ \text{LT Debt/Assets}^{\langle - \rangle} + \Delta\text{Current Ratio}^{\langle + \rangle} + \text{Share Issuance}^{\langle - \rangle} \\ &+ \Delta\text{Op Mgn}^{\langle + \rangle} + \Delta\text{Asset Turnover}^{\langle + \rangle}. \end{aligned} \tag{5}$$

Unlike the other strategies here presented, this investment strategy uses binary scaling. The top 20% B/M stocks of the STOXX 600 are binary scaled by the nine factors[1] shown, either in ascending or descending order, to yield a one or a zero in each case, according to Sect. 2.1. The nine binary values are added together to produce a score from 0 to 9 for each stock. The top stocks scored 9 or 8 are bought whereas the bottom stocks scored 0 or 1 are sold short, for one year.

2.6 Magical Bambu

The development of the Magical Bambu (MB) trading strategy stemmed from empirical tests aiming to optimise the interplay of various factors, seeking to align with the hypothetical preferences of an investor who balances return and risk. This approach assumes that the market conditions in our dataset are representative of future outcomes. So, the Magical Bambu investment strategy aimed to incorporate additional asset-focused fundamental factors into the Magic Formula, alongside the technical factor of Winners and Losers, and selecting fewer companies. The strategy involved exchanging the ROC factor from the Magic Formula for ΔROA and ΔAsset Turnover factors from (Piotroski 2000). These factors are considered better for defining valuable assets and their variation in value between two consecutive years. The Yield factor of the Dogs of the Dow and supported in academic works (Fama and French 1992; Singh and Walia 2022), was also considered. The strategy included the technical RS 6 m factor to combine value with momentum, inspired by recent studies such as (Siirtola 2021). The corresponding ranking formula is:

$$\begin{aligned} score_r =& \text{Earnings Yield}^{\langle + \rangle} + \text{Yield}^{\langle + \rangle} + \Delta\mathrm{ROA}^{\langle + \rangle} \\ &+ \Delta\text{Asset Turnover}^{\langle + \rangle} + \text{RS 6m}^{\langle + \rangle}. \end{aligned} \tag{6}$$

Stocks from the STOXX 600, excluding financials and utilities, are ranked separately by five factors in ascending order: Earnings Yield, Yield, ΔROA, ΔAsset Turnover and RS 6 m. Earnings Yield and Yield are the same factors used in respectively (3) and (2), while RS 6 m is the same technical factor used in (4). ΔROA and ΔAsset Turnover are the same factors used in (5). The five ranks are added together to produce a final

[1] ROA is Return on Assets, OCF is Operating Cash Flow, ΔROA is the difference between current and last year's ROA, Accrual Ratio is calculated as (Net Income - Free Cash Flow) divided by Total Assets, ΔLT Debt/Assets is the difference between current and last year's Long Term Debt to Assets ratio, ΔCurrent Ratio is the difference between current and last year's Current Ratio, Share Issuance the dollar amount of shares issued in the current year, ΔOp Mgn is the difference between current and last year's Operating Profit Margin, ΔAsset Turnover is the difference between current and last year's Asset Turnover ratio, see (Piotroski 2000).

score, from which stocks are ranked, with the top 20 invested for 1 year, after which this process is repeated.

3 Computational simulation

3.1 Experimental setting

The specific formulation of (1) varies for each factor-based strategy. We ran the four classic strategies using the appropriate ranking formulas for each (Sect. 2) and examined their investment results in a financial sample based on the STOXX Europe 600[2]. During each rebalance, which occurs at the start of each calendar year or semester, the exact same strategy is applied to the current constituents of the STOXX 600 index, to invest in the top (bottom) stocks as selected by their respective formulas. Any gains/losses from previous investments are reinvested. To repurpose the classic strategies for this index, we had to make slight modifications to the original strategies, as described in the previous section.

The financial sample was extended to cover the 10.5-year period from 2014 to June 2024, encompassing significant events such as the 2018 market crash, the worldwide COVID-19 pandemic along with its lasting after-effects and the war in Ukraine. The year 2018 experienced considerable turmoil and downturns driven mainly by a combination of factors, including the escalating U.S.-China trade war, rising interest rates imposed by central banks, the unpredictable nature of Brexit negotiations, and various global economic uncertainties, all of which had notable repercussions on European markets. Additionally, the period of 2020–2022 was profoundly marked by the global COVID-19 pandemic, which brought unprecedented challenges to economies worldwide, leading to widespread lockdowns, disruptions in supply chains, and significant shifts in consumer behavior. Finally, the war in Ukraine, which began in February 2022, triggered significant market downturns, particularly in Europe. The financial sample also aims to capture the gradual recovery phases and the implementation of fiscal and monetary policies designed to mitigate the economic impact during these challenging times.

This financial sample was assembled using datasets from three different sources:

- Market data (the so-called daily OHLCV[3]) was obtained from Yahoo! Finance,[4] a well-known free provider of daily stock prices with global coverage.

[2] The STOXX 600 index (https://qontigo.com/index/SXXGR/) is widely used in Europe to track the broad European market. It consists of 600 constituents representing the largest European companies by market capitalization, not limited to the Eurozone. The largest represented countries are the UK, with around 200 companies, followed by Germany and France, with around 100 companies each, then Sweden, Switzerland and Italy, with more than 40 companies each. Additionally, companies from 13 other European countries are also represented, including Poland and the Czech Republic from Eastern Europe. The index is owned and maintained by STOXX Ltd., part of the Deutsche Börse Group.

[3] Open, High, Low, Close, Volume.

[4] https://finance.yahoo.com.

- Fundamental data, which includes company financials such as those found on income statements, balance sheets, and cash flow statements reported on a half-yearly/yearly basis, was downloaded from Robur Data Encoding through Nasdaq Data Link.[5] Robur is a provider of harmonised financials and ratios for over 8,700 of the most liquid global stocks, with a focus on Asia and Europe.
- STOXX Europe 600 constituents, which is a list of all constituents of the index issued on a quarterly basis, was provided by STOXX Ltd. The constituents of the STOXX 600 index represent the stock universe from which the ranking formulas for each investment strategy select their stocks.

The three datasets were assembled and harmonised into an unified financial sample. The factors required for stock selection were computed using data from 2014, the first year of the sample. As a result, investments using the respective ranking formulas based on (1) only began from 2015 onwards. To calculate certain factors (such as ΔROA, ΔAsset Turnover, among others) that require at least two years of historical data, we downloaded fundamental data from Robur dating back to 2010.

The risk-free rate in the sample, 0.09%, was calculated based on the average of 1-year maturity bonds from AAA-rated Euro area countries, as published by the European Central Bank (ECB).

As we evaluate each classic factor-based strategy within this European sample, we compare their investment results with those of the Market, the STOXX Europe 600, for benchmarking. To obtain these investment results, all the assets selected from the STOXX 600 index by their respective formulas are invested with different weights. Four approaches were taken: the Equally Weighted Portfolio (EWP) where the weight is equal for all assets, the Value-Weighted Portfolio (VWP) where the weights are proportional to the asset's market capitalization and two efficient portfolios from CAPM: the Minimum Variance Portfolio (MVP) and the Market Portfolio or Tangent Portfolio (MKTP) (Huang and Litzenberger 1988). Each forms a weighted portfolio of stocks that is rebalanced on a periodical basis. Notice that the same assets are shared among all four portfolios: EWP, VWP, MVP, and MKTP for a given strategy at each rebalance. The only difference is how the weights are distributed among the assets. The MVP and MKTP assign negative weights to some of the assets, turning into long-short portfolios, with the sum of the weights being equal to 1. For the long-only classic strategies, DoD, MF, and MB, all weights sum to 1 in every portfolio of theirs. For the long-short classic strategies, WL and F-Score, which hold an equally-weighted portfolio of assets in long and short positions, the sum of the weights of their EWP and VWP portfolios is 0 or close to 0, whereas their MVP and MKTP weights sum to 1.

Several profit measures are used for evaluating investment performance in Qrumble. Qrumble is a computational tool for efficient strategy experimentation, aimed at combining and testing diverse metrics for factor-based investing.[6] Precisely we consider performance metrics from the CAPM (Huang and Litzenberger 1988): Alpha, Beta and Sharpe ratio, complemented with risk metrics Value at Risk (VaR) and Tail

[5] https://data.nasdaq.com/databases/RB1/data.

[6] Qrumble: A Python framework documented in https://bit.ly/Qrumble.

Table 1 Total results on the 9.5-year investment based on Dogs of the Dow strategy

	ROI % (annual)	Mean %	St Dev %	Sharpe	Beta	Alpha %	VaR/1y %	TVaR/1y %
EWP	**86.62 (6.79/1y)**	**7.87**	17.07	**0.46**	0.95	**−4.92**	24.55	40.59
VWP	81.08 (6.45/1y)	7.63	17.45	0.43	*0.96*	−8.13	24.77	41.37
MVP	50.49 (4.40/1y)	5.57	**16.49**	0.33	**0.79**	−13.52	**23.42**	**38.68**
MKTP	*−23.90 (−2.83/1y)*	*4.60*	*38.35*	*0.12*	0.86	*−29.47*	*60.78*	*94.57*

The optimal values for each measure are highlighted in bold or italic
EWP (Equal-Weighted); VWP (Value-Weighted); MVP (Minimum Variance); MKTP (Market Portfolio)

Value at Risk (TVaR) (Jorion and GARP 2007). We also consider the mean that calculates the expected return and Return on Investment (ROI) that quantifies efficiency by assessing gains or losses relative to the initial investment, expressed as a percentage. Annualised Return converts returns over a specific period into an annualised percentage, facilitating comparisons across investments. Alpha indicates the stock's historical performance compared to the expected return estimated. Beta is a measure of the relation between the risk of the portfolio and the risk of the market. The Sharpe ratio, in turn, balances both profit and risk aspects into a single comprehensive measure. VaR estimates potential losses with a specified confidence level, measuring downside risk, while TVaR takes into account extreme loss scenarios, assisting in the evaluation of tail risk. Finally, we fix the profile of an investor by setting a mean-variance utility function and determine their optimal portfolio for each strategy.

3.2 Dogs of the Dow results

We initiated our empirical tests by examining our adaptation of the Dogs of the Dow (DoD) strategy for European stocks. In the 9.5-year investment analysis, Table 1 shows that EWP outperformed with the highest ROI, mean returns, Sharpe ratio and alpha among the portfolios. Conversely, MVP presented the lowest standard deviation, which translated to the lowest VaR and TVaR. However, the differences between the top two portfolios, EWP and VWP, were relatively minor. MKTP struggled, delivering a negative ROI, and very high risk metrics. Interestingly, portfolios with lower betas, such as MVP and MKTP, had lower Sharpe values and lower negative alphas, providing an unconventional insight. The pursuit of theoretically efficient portfolios didn't yield the anticipated results, in the way that EWP and VWP displayed similar risk metrics to MVP but achieved superior ROI and Sharpe ratios, underscoring the need for a comprehensive evaluation of portfolio performance.

Figure 1 compares the cumulative returns of the top three portfolios against the market from 2015 to June 2024. Due to the MKTP portfolio's high volatility, which would flatten the other curves, it is displayed in Sect. 3.7, along with the cumulative return figures of all MKTP portfolios. According to Fig. 1, the market shows the highest returns, leaning towards 120% by mid 2024. Since 2018, one could say that the market had an advantageous "starting point" and was able to continuously surpass the three weighted portfolios of the DoD, even during 2020 and after. The EWP and

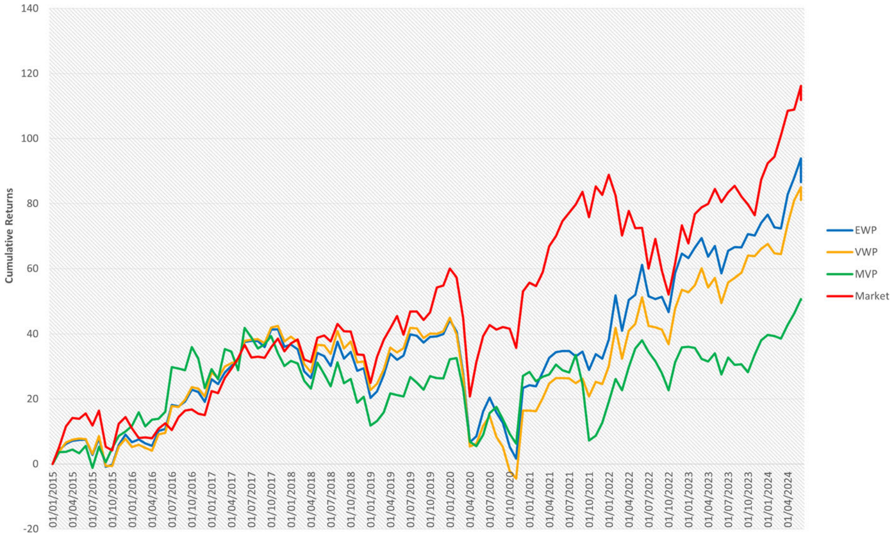

Fig. 1 Cumulative returns evolution of the Dogs of the Dow strategy in Europe with varying weight portfolios

VWP closely track each other, achieving around 90%, while MVP lags behind at 50%, reflecting its lower-risk/lower-expected return strategy. Overall, the results highlight the trade-off between risk and return, with the market outperforming the portfolios.

The broader market appears to recover more swiftly post-COVID and post-outbreak of the war in Ukraine compared to the Dogs of the Dow (DoD) strategy, which annually selects only 10 large-cap companies. Although the market suffered a steeper initial downturn after the war began, it consistently outperformed the DoD portfolios during rebounds. In periods of instability, the overall market exhibits greater resilience and ability to recover compared to these highly specialised portfolios.

3.3 Magic Formula results

In evaluating Table 2, we observe stark performance differences among the portfolios that went through the Magic Formula strategy. The MKTP achieves the highest ROI

Table 2 Total results on the 9.5-year investment based on the Magic Formula strategy

	ROI % (annual)	Mean %	St Dev %	Sharpe	Beta	Alpha %	VaR/1y %	TVaR/1y %
EWP	*128.64 (9.10/1y)*	9.82	16.25	0.60	0.95	13.75	24.41	39.09
VWP	152.77 (10.25/1y)	**10.64**	14.96	**0.71**	0.81	33.80	22.76	35.15
MVP	132.60 (9.29/1y)	9.76	**14.76**	0.66	**0.66**	**38.16**	**22.37**	**33.45**
MKTP	**1837 (36.61/1y)**	*−126156*	*383622*	*−0.33*	*−69.18*	*−315567*	*295.31*	*161991*

The optimal values for each measure are highlighted in bold or italic

EWP (Equal-Weighted); VWP (Value-Weighted); MVP (Minimum Variance); MKTP (Market Portfolio)

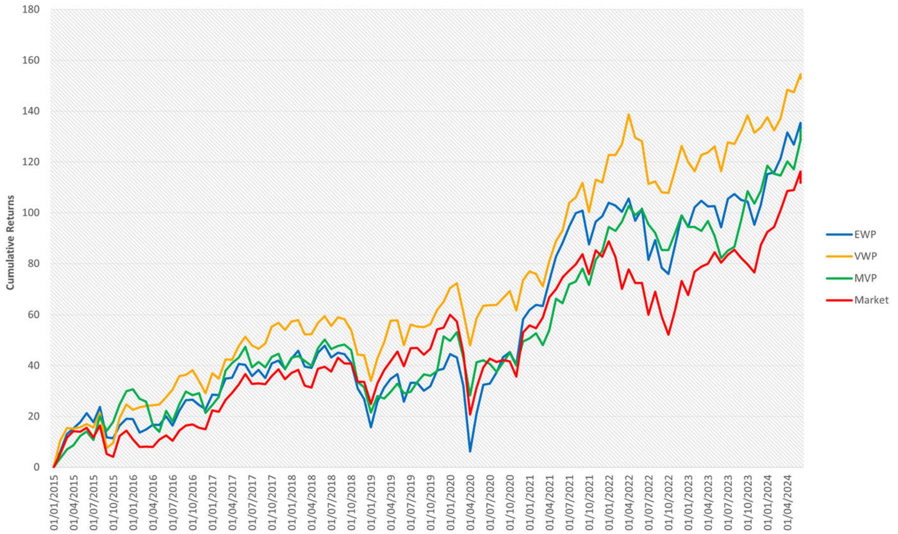

Fig. 2 Cumulative returns evolution of the Magic Formula strategy in Europe with varying weight portfolios

but falters terribly in all risk (-adjusted) metrics while also yielding the lowest mean returns. The other three portfolios demonstrate markedly superior results in these metrics. Our backtest results reveal that the MF's MKTP portfolio assigns exceptionally high weights to its assets (i.e., high leverage), rendering it extremely volatile. This volatility phenomenon, which afflicts all MKTP portfolios — particularly the MF, WL, and F-Score strategies — is discussed in greater depth in Sect. 3.7.

When comparing the remaining three portfolios, we find relatively minor disparities, especially in mean, standard deviation, and risk measures such as VaR and TVaR. Out of the three, EWP ranks at the bottom, with the lowest scores in ROI, Sharpe, and alpha. MVP maintains its lowest risk measures across the board. VWP overperforms the others in (risk-adjusted) returns.

Figure 2 compares the cumulative returns of three portfolios against the market from 2015 to June 2024. Again, due to the MKTP portfolio's high volatility, which would flatten the other curves, it is displayed in Sect. 3.7. The VWP outperforms all other portfolios and the market, achieving nearly 160% cumulative returns by mid-2024. This suggests that the value-weighted strategy — investing in the 30 best-valued European stocks annually (as ranked by the Magic Formula) — yielded the most robust growth over the period. The EWP (blue line) and MVP (green line) show more moderate performance, with cumulative returns approaching 140% by mid-2024, indicating solid growth. The MVP, designed to minimize risk, matches EWP's performance with lower risk. The market (red line) lags behind the portfolios, ending just under 120% cumulative returns by the investment period's end. Despite its strong post-2020 and post-2022 recoveries seen in the DoD case, the market trails the VWP here, highlighting the value-weighted strategy's advantages over the broader market index during this timeframe. Overall, the figure demonstrates the VWP's superior returns, while the EWP and MVP offer more stable growth, with the market underperforming in comparison.

3.4 Buying Winners and Selling Losers results

The simulation of the Buying Winners and Selling Losers strategy (WL) revealed some intriguing results in Table 3. Over the 9.5-year investment period, the EWP outperformed the others in ROI. However, the MVP emerged as the overall top performer in achieving the highest mean return, Sharpe ratio, and alpha. Surprisingly, in this strategy, the MVP didn't secure the best risk metrics, which was claimed instead by the VWP. Backtest results unveiled an anomaly: during the mid-2020 rebalance, the MVP unusually assigned weights approximately 40 times higher than normal to its 120 assets (60 winners plus 60 losers). This exceptional allocation made the MVP extremely volatile in the second half of 2020, as clearly illustrated in Fig. 3. This singular instance stands out, as no other rebalance in any strategy had ever reached

Table 3 Total results on the 9.5-year investment based on Buying Winners and Selling Losers strategy

	ROI % (annual)	Mean %	St Dev %	Sharpe	Beta	Alpha %	VaR/1y %	TVaR/1y %
EWP	**93.35 (7.19/1y)**	8.35	19.39	0.43	0.21	63.35	28.07	41.32
VWP	52.49 (4.54/1y)	*5.95*	**16.93**	0.35	**0.02**	*56.31*	**24.84**	**36.59**
MVP	42.50 (3.80/1y)	**64.96**	140.81	**0.46**	0.67	**573.86**	32.09	171.46
MKTP	*−756.08*	30.10	*587.25*	*0.05*	*1.95*	124.96	*403.85*	*1285.19*

The optimal values for each measure are highlighted in bold or italic

EWP (Equal-Weighted); VWP (Value-Weighted); MVP (Minimum Variance); MKTP (Market Portfolio)

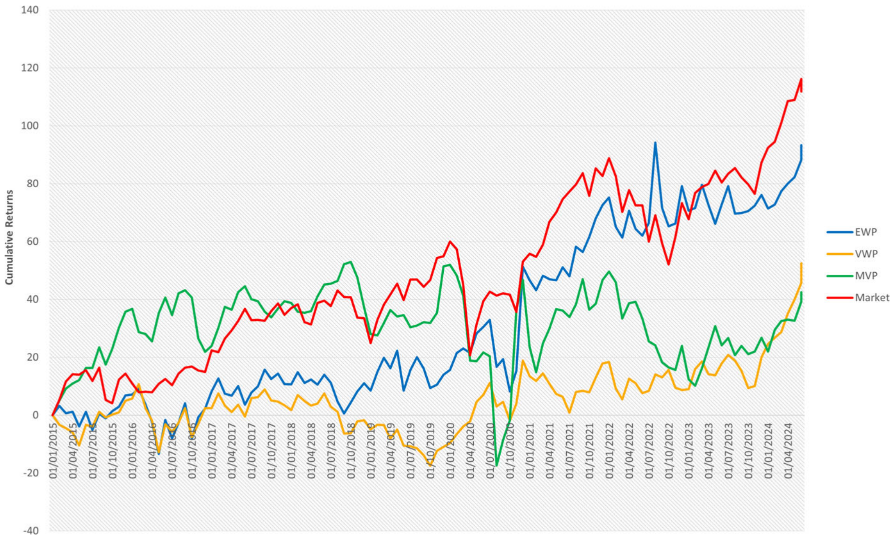

Fig. 3 Cumulative returns evolution of the Buying Winners and Selling Losers strategy in Europe with varying weight portfolios

such high weight assignments for MVP during the study. It also significantly worsened the MVP's overall risk metrics. In stark contrast, the MKTP demonstrated the poorest overall performance, registering the lowest ROI and Sharpe ratio, along with exceptionally poor risk metrics. Backtest analysis revealed that the MKTP portfolio consistently employed high leverage at each rebalance, leading to extreme volatility in the subsequent six-month periods.

The analysis of Fig. 3 highlights the challenges in outperforming the market. Only the MVP showed sporadic potential to surpass the benchmark, doing so in two distinct periods: from September 2015 to November 2016 and at the end of 2018. The anomalous event in mid-2020 slightly disrupted its performance, but by then, MVP was already trailing the market — a gap that would continue to widen in subsequent months. The EWP managed to achieve nearly 100% cumulative returns by mid-2024, significantly outperforming the other portfolios, but falling short of the market. In contrast, the VWP exhibited the weakest performance in this graph, consistently hovering at the bottom. Overall, during this period, the weighted portfolios employing the Buying Winners and Selling Losers strategy failed to meet expectations, consistently lagging behind the market benchmark.

3.5 F-Score results

Our analysis of the F-Score strategy simulation over the 9.5-year investment period reveals again intriguing results. Examining Table 4, we find that the MKTP portfolio achieved outstanding ROI, mean return, alpha and the highest Sharpe ratio in the study. This exceptional performance stems from extreme leverage, which allocated very high weights to a relatively small number of assets each year (stocks scoring highest and lowest on the F-Score formula). This approach yielded positive results for the F-Score strategy, contrasting sharply with the negative outcomes observed in the WL strategy presented earlier, which invests in far more stocks per rebalance. However, the MKTP's stellar performance came at a cost — it exhibited the worst risk metrics across the board. Conversely, the MVP portfolio maintained its characteristic low-risk profile, achieving the lowest risk metrics overall. Initially, the variations in portfolio weightings may appear to have little impact on the first three portfolios. However, upon closer examination, VWP emerges as a standout performer, second only to MKTP, when considering (risk-adjusted) returns.

Table 4 Total results on the 9.5-year investment based on the F-Score strategy

	ROI % (annual)	Mean %	St Dev %	Sharpe	Beta	Alpha %	VaR/1y %	TVaR/1y %
EWP	*103.90 (7.79/1y)*	*9.55*	21.16	*0.45*	0.69	33.64	34.05	47.93
VWP	193.83 (12.01/1y)	13.24	20.87	0.63	**0.55**	82.04	32.64	47.76
MVP	138.77 (9.59/1y)	10.99	**20.25**	0.54	0.96	*24.26*	**28.46**	**47.59**
MKTP	**9062 (60.89/1y)**	**2345**	*2506*	**0.94**	*−9.88*	**23716**	*405.97*	*1317.24*

The optimal values for each measure are highlighted in bold or italic

EWP (Equal-Weighted); VWP (Value-Weighted; MVP (Minimum Variance); MKTP (Market Portfolio)

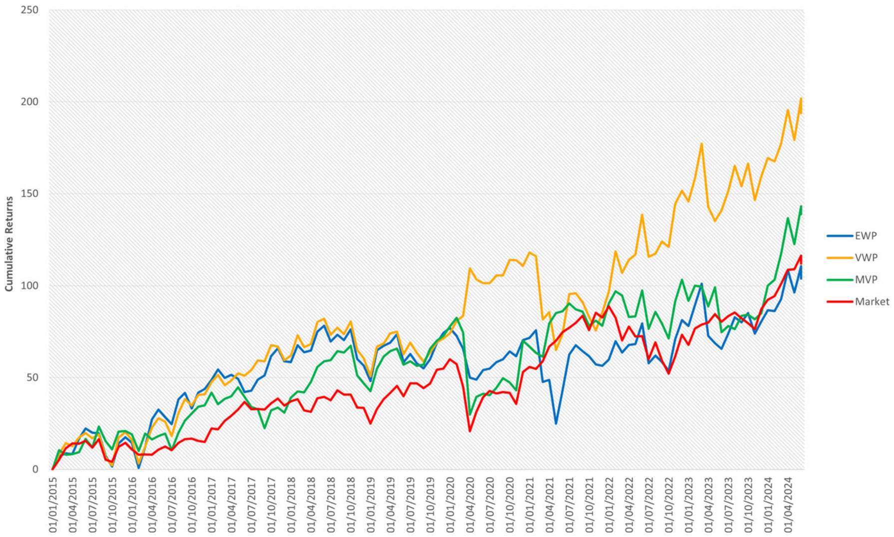

Fig. 4 Cumulative returns evolution of the F-Score strategy in Europe with varying weight portfolios

Figure 4 omits the MKTP portfolio due to its extreme volatility, which would have flattened the other curves. All MKTP results are presented in Sect. 3.7. An analysis of Fig. 4 reveals the VWP's superior performance compared to other portfolios and the market benchmark, reaching 200% at the middle of 2024. Notably, when COVID-19 struck, the VWP exhibited an upward trend instead of declining, decisively outpacing the other curves from that point forward. Furthermore, the market downturn triggered by the war in Ukraine had minimal impact on this portfolio. The EWP and MVP portfolios maintained an advantage over the market until the COVID-19 pandemic struck. Both portfolios subsequently recovered and weathered the war in tandem with the market. This is noteworthy considering that the F-Score strategy selects only a small number of assets each year — the top and bottom scorers on Piotroski's F-Score formula, rarely exceeding a dozen stocks per rebalance — yet manages to rebound from the pandemic and war outbreak as effectively as the broad European market. By mid-2024, the MVP narrowly outpaced the market, ending with nearly 150% cumulative return, while the EWP finished on par with the market.

3.6 Magical Bambu results

Regarding our computational simulation with the new tailor-fit illustrative strategy Magical Bambu (MB), Table 5 displays the MKTP with the highest ROI, mean, and alpha. Meanwhile, the VWP obtained the top Sharpe ratio and second-highest ROI, making this portfolio a remarkable overperformer. True to form, the MVP maintained the lowest standard deviation, beta, VaR, and TVaR. As expected, the MKTP had the worst standard deviation, VaR, and TVaR, but here the differences relative to the other portfolios were comparatively smaller. This suggests the MKTP portfolio didn't employ excessive leverage — a finding corroborated by our backtest data. The overall

Table 5 Total results on the 9.5-year investment based on Magical Bambu strategy

	ROI % (annual)	Mean %	St Dev %	Sharpe	Beta	Alpha %	VaR/1y %	TVaR/1y %
EWP	172.53 (11.13/1y)	11.95	18.16	0.65	*0.99*	*31.59*	27.88	43.70
VWP	259.82 (14.43/1y)	14.61	17.09	**0.85**	0.83	70.88	26.60	40.76
MVP	*138.38 (9.58/1y)*	*10.14*	**15.63**	0.64	**0.70**	38.38	**24.21**	**36.63**
MKTP	**372.75 (17.76/1y)**	**23.74**	*39.75*	*0.60*	0.86	**157.39**	*53.90*	*91.40*

The optimal values for each measure are highlighted in bold or italic
EWP (Equal-Weighted); VWP (Value-Weighted); MVP (Minimum Variance); MKTP (Market Portfolio)

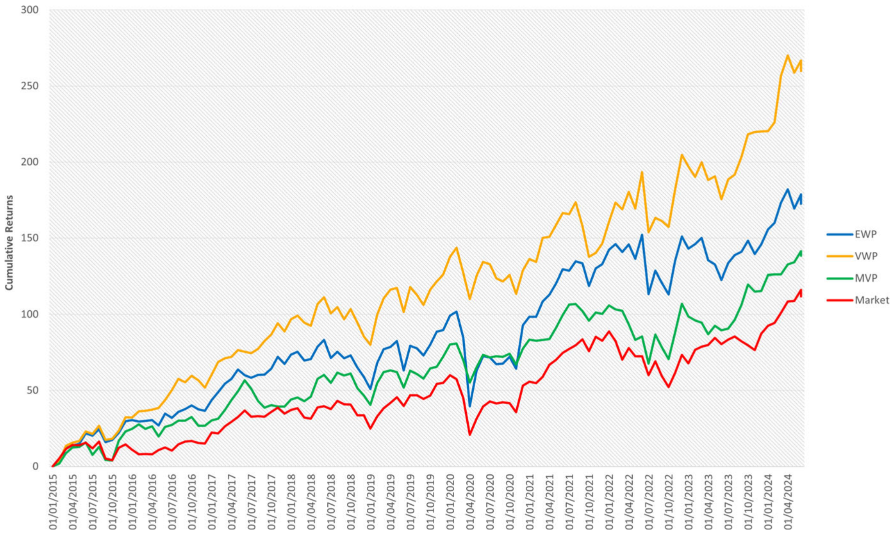

Fig. 5 Cumulative returns evolution of the Magical Bambu in Europe with varying weight portfolios

table metrics reveal that this strategy generated exceptional profits over the 9.5-year period, particularly when compared to previous strategies. Remarkably, it maintained relatively stable risk levels across all portfolios, including the historically volatile MKTP.

Simply put, Fig. 5 clearly demonstrates the consistency of the Magical Bambu strategy. All holdings within this strategy consistently outperformed the market benchmark, effectively weathering the 2018 market crash, the COVID-19 pandemic and the war in Ukraine. With the MKTP results in Sect. 3.7, the VWP emerges as the top performer from the outset, reaching above 250% at the end of the investment. Notably, all MB's portfolios exhibit a similar pattern, consistently outperforming the market. This chart illustrates the robustness of the Magical Bambu approach.

3.7 MKTP results

Figures 6 and 7 illustrate the cumulative returns evolution of the MKTP portfolios

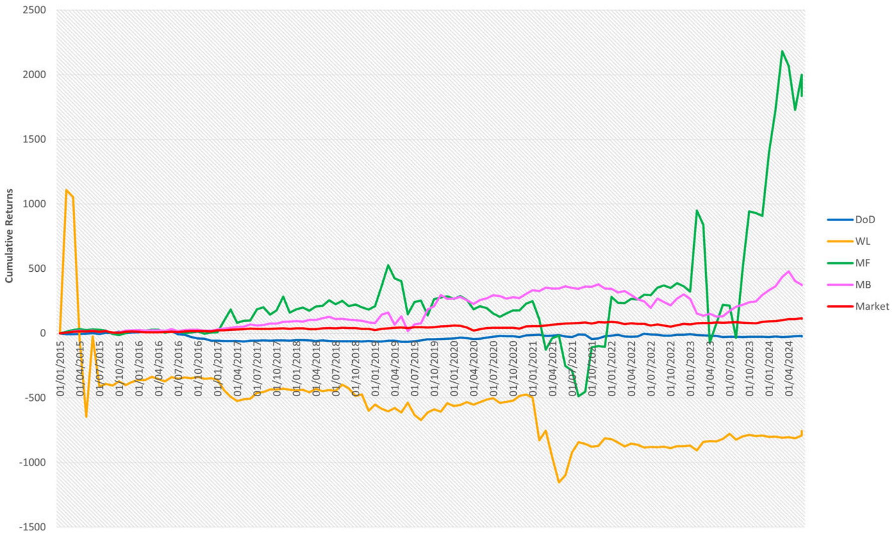

Fig. 6 Cumulative returns evolution of the strategies' MKTP portfolios in Europe, without the F-Score

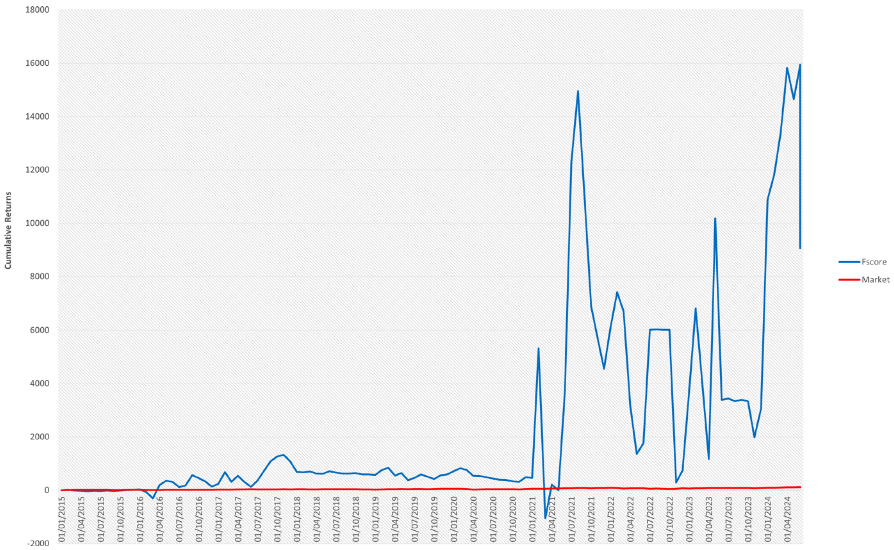

Fig. 7 Cumulative returns evolution of the MKTP portfolio for the F-Score strategy in Europe

across the various strategies. These figures have been located to this section to prevent the flattening of other portfolio curves and to maintain their visibility. Figure 7 exclusively presents the MKTP portfolio for the F-Score strategy. This isolation was necessary due to its exceptional volatility, which would have overshadowed even the performance of all other MKTP strategies combined in Fig. 6. By presenting these results separately, we can better appreciate the unique characteristics and extreme fluctuations of each MKTP portfolio while maintaining the clarity of the overall analysis.

As both figures illustrate, all MKTP portfolios exhibited extreme volatility. This volatility varied by strategy, as some strategies demonstrated a stronger effect, while others showed a milder impact. To understand this phenomenon, we analyzed the weights in all MKTP portfolios. We focused on the sum of positive weights, as the sum of negative weights in the MKTP portfolios is simply 1 minus this sum. We refer to the sum of positive weights as the portfolio's *leverage*. A portfolio is considered leveraged when this sum exceeds 1. If it significantly exceeds 1 — say, around 30 — we describe the portfolio as highly leveraged, indicating a ≈30x leverage in this case. Our analysis revealed that for certain strategies, notably MF, WL, and F-Score, their MKTP portfolios were extremely leveraged at times. We observed instances (rebalances) where the MKTP reached staggering levels of leverage:

- ≈30x leverage (MF in 2017 and 2023; WL in mid-2018; F-Score in 2016).
- ≈50x leverage (WL in 2017 and mid-2020; F-Score in 2023).
- ≈70x leverage (MF in 2021).
- ≈100x leverage (F-Score in 2021).
- ≈150x leverage (WL in 2021).

The WL strategy's MKTP portfolio reached the highest leverage, peaking at ≈300x in 2015. In stark contrast, the MKTP portfolios for DoD and MB demonstrated more tamely behavior, maintaining leverage within a modest 1.5–5x range.

4 Discussion

Comparing Various Strategies with Different Portfolios. The study evaluated portfolio weighting strategies like EWP, VWP, MVP and MKTP, focusing on performance metrics. The same assets were shared among all four portfolios for a given strategy at each rebalance. The difference was in the distribution of weights, whose sum is always one.[7] MVP and MKTP nearly always involved a mix of long and short positions (positive and negative weights), with the sum of the positive weights largely exceeding 1, especially for MKTP. Due to excessive leverage, MKTP cannot be considered beyond a theoretical portfolio, rendering it impractical for use in investment banking. Consequently, further discussion will not involve MKTP.

Our computational simulation yielded several key findings across different investment strategies. The DoD strategy underperformed the market across all portfolio weighting schemes, with its EWP performing slightly better than the others. For the MF strategy, its VWP outperformed both the market and other portfolios (this discussion excludes MKTP). While the MVP exhibited the lowest risk metrics, the minimal risk difference between MVP and VWP makes it challenging to recommend MVP despite its slightly lower risk profile. Portfolios based on the WL strategy consistently underperformed the market. Its EWP showed marginally better returns on investment (ROI) compared to the other portfolios but still fell short of the market benchmark. WL

[7] The exceptions were the EWP and VWP for the long-short strategies: WL and F-Score. Their overall sum was around 0 because the assets' weights were fairly balanced between the long and short positions.

was the only strategy that selected over a hundred stocks at each rebalance, while other strategies settled for 30 or less. In the F-Score strategy, the VWP again outperformed the other portfolios, including the market. The MVP maintained its characteristic low-risk metrics in terms of standard deviation, VaR, and TVaR. For the MB strategy, the VWP emerged as the top performer once more, while the MVP exhibited the lowest risk metrics as expected. Remarkably, the MB was the only strategy where all the portfolios consistently surpass the market benchmark in the tested sample—a noteworthy achievement.

Table 6 presents a comparative meta-analysis per strategy/portfolio. We use the Sharpe ratio (SR) to compare the risk-adjusted returns across all strategies and portfolios. Additionally, to better evaluate the optimal investment strategy based on the investor's risk aversion profile, we employ a utility function (U). This utility function effectively conveys mean-variance preferences for an investor, balancing risk and return in line with modern portfolio theory. To apply this function, we assign each investor a risk aversion coefficient, denoted A, ranging from 1 (lowest risk aversion) to 5 (highest risk aversion). The utility function is as follows:

$$U = \overline{R} - 0.5 \times A \times \sigma^2, \tag{7}$$

where U is the utility score of the investment, A is the investor's risk aversion coefficient, $\overline{R}$ is the mean annual return of the portfolio, and σ^2 is the variance. The portfolio with the highest utility score is considered the best portfolio for that type of investor.

The Magical Bambu (MB) strategy's superior performance is evident in Table 6. Its VWP portfolio boasts the highest Sharpe ratio among all strategies and portfolios analyzed—excluding the MKTP for the F-Score, which exhibited extreme volatility (as shown in Fig. 7). It also achieved the highest utility scores across a wide range of risk aversion profiles (A=1, 3, 5)—again, excluding the MKTP for MB, which scored higher for investors with high risk tolerance (though MKTP portfolios are impractical to implement). With top utility scores among all strategies and portfolios, the VWP portfolio of Magical Bambu emerges as the prime recommendation for investors seeking exposure to the broad European market during this period, regardless of risk aversion profile. This timeframe is particularly significant, encompassing three major crises: the 2018 downturn triggered by Brexit, the COVID-19 pandemic with its lasting effects and the war outbreak in Ukraine. While these crises affected all strategies and portfolios to varying degrees, MB distinguishes itself through consistent outperformance.

Magical Bambu. The Magical Bambu investment strategy seems to point to high profits without much higher risk, and all tested weighting schemes (portfolios) outperformed the market. For a wide range of risk-profile investors, it achieved the highest utility score of all the strategies/portfolios under test. Magical Bambu's effectiveness stems from its unique blend of fundamental and technical factors. However, such strategies often lose their edge once widely adopted. While the underlying rationale remains sound, their effectiveness may deteriorate across various markets and time periods moving forward. It is important to note that the results depend on the dataset, which, although diverse, cannot guarantee performance across all market behaviors.

Table 6 Sharpe ratio/Utility score comparison across investment strategies and portfolios, for investors with high, moderate, and low risk aversion profiles

	DoD		MF		WL		F-Score		MB	
	SR U^5	U^3 U^1	SR U^5	U^3 U^1	SR U^5	U^3 U^1	SR U^5	U^3 U^1	SR U^5	U^3 U^1
EWP	0.46	3.50	0.60	5.86	0.43	2.71	0.45	2.83	0.65	7.00
	0.59	6.41	3.22	8.50	−1.05	6.47	−1.64	7.31	3.71	10.30
VWP	0.43	3.06	0.71	7.28	0.35	1.65	0.63	6.71	**0.85**	**10.23**
	0.02	6.11	5.04	9.52	−1.22	4.52	2.35	11.06	**7.31**	**13.15**
MVP	0.33	1.49	0.66	6.49	0.46	−232.45	0.54	4.84	0.64	6.48
	−1.23	4.21	4.31	8.67	−430.73	−34.18	0.74	8.94	4.03	8.92
MKTP	0.12	−17.46	0.33	-2.21×10^9	0.05	−5142.84	***0.94***	-9.19×10^4	0.60	0.04
	−32.17	−2.75	-3.68×10^9	-7.36×10^8	−8591.46	−1694.21	-1.55×10^5	-2.91×10^4	−15.76	***15.84***

The optimal values for each measure are highlighted in bold or italic
Sharpe ratio (SR) and Utility scores for varying risk aversion profiles: high (U5), moderate (U3), and low (U1)
EWP (Equal-Weighted,)VWP (Value-Weighted), MVP (Minimum Variance), MKTP (Market Portfolio)

In crafting Magical Bambu, we carefully selected key factors from established investment strategies, resulting in a combination that yields consistently high returns with comparable risk. The strategy leverages Earnings Yield to identify companies with strong earnings relative to their price. It also incorporates asset-focused metrics like ΔROA and ΔAsset Turnover, which gauge a company's profitability relative to its total assets—essentially measuring how efficiently it manages its balance sheet to generate profits and revenue. Finally, it combines value investing with momentum—a potentially controversial approach that makes this strategy a compelling subject for discussion.

5 Conclusions

This work aimed to test different configurations of various baseline strategies using the new Qrumble framework. The Qrumble framework was essential to add and study two theoretically efficient portfolios, and create a new multi-factor investment strategy in the largest European stock market from 2015 to June 2024. This paper emphasizes the wide range of possible strategies and portfolio weighting schemes, which encompasses a broad type of investors and their preferences and objectives, appealing to individual and corporate investors or brokers. This was mostly possible due to a broad portfolio comparison through several metrics, weights and factor fusion.

Our work has potential applications in investment banking. While the MKTP portfolios remain theoretical constructs, impractical for real-world implementation, the other three weighting schemes—equally-weighted, value-weighted, and minimum variance portfolios—are readily applicable. Investment banks can adopt these practical portfolios for any of the strategies we've examined, offering versatile options for real-world implementation across diverse investment approaches. However, before implementation, it's crucial to carefully select and calibrate the appropriate investment strategy for each investor's profile. Further testing is essential, particularly when considering the suitable investment universe for each institution. We've already applied various risk metrics in this study, such as Value at Risk and Tail Value at Risk, which can be easily incorporated into each institution's specific requirements.

In this 9.5-year computational simulation, the Magical Bambu trading strategy stands out, particularly in metrics like the utility score and Sharpe ratio. It achieved the highest utility scores in its VWP portfolio formulation for a wide range of investor risk-profiles and the highest unleveraged Sharpe ratio, showcasing its potential for excellence. The usage of fundamental factors that measure the yearly differences in certain aspects of each business could be a more impartial and fair approach for comparison and selection, due to the variability among companies. After all, the usage of both fundamental and technical analysis can generate impressive outcomes. However, backtests over limited periods can only reveal certain features. Investors should tailor strategies to their unique preferences and objectives. This study serves as a blueprint for creating personalized approaches. The focused examination of Magical Bambu's success underscores the advantages of such customization within the 2015–June 2024 market conditions in Europe. Notably, investors seeking higher returns on investment might be willing to accept more risk, emphasizing the necessity of adaptability to individual risk appetites and goals. As such, future adaptations should be approached with a nuanced understanding of each investor's specific requirements and risk tolerance, considering the forecasted market conditions at that time.

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