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FACTOR-BASED STOCK SELECTION AND MEAN-VARIANCE PORTFOLIO OPTIMIZATION: AN EMPIRICAL STUDY OF BISNIS-27

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ABSTRAK

Di tengah pertumbuhan yang signifikan dari produk exchange-traded fund (ETF) di Indonesia, pangsa pasar ETF masih tergolong rendah, yaitu sekitar 1% dari total dana kelolaan industri reksa dana. Hal ini sebagian disebabkan oleh mayoritas produk ETF hanya mereplikasi indeks secara pasif sehingga menawarkan *risk-adjusted return* yang terdiferensiasi secara terbatas. Penelitian ini mengusulkan dan menguji secara empiris kerangka konstruksi portofolio factor investing dengan optimalisasi mean-variance yang diterapkan pada konstituen Indeks Bisnis-27. Pada tahap pertama, seluruh 27 saham konstituen diberi skor dan diperingkat menggunakan model multi-faktor komposit yang mencakup faktor growth, quality, value, momentum, dan volatility, yang distandarisasi menggunakan z-score untuk kemudian dipilih 15 saham teratas berdasarkan skor tertinggi. Optimalisasi mean-variance diterapkan pada 15 saham terpilih menggunakan Solver untuk memperoleh bobot optimal berdasarkan *risk-adjusted return*. Portofolio dievaluasi secara in-sample sepanjang periode observasi November 2021 hingga April 2025 menggunakan imbal hasil bulanan aktual, dan dibandingkan dengan pembobotan *equal weight*, factor score, dan minimum variance, serta Indeks Bisnis-27. Hasil penelitian menunjukkan bahwa saham hasil seleksi faktor mengungguli tolok ukur, di mana optimalisasi mean-variance menghasilkan Sharpe ratio 1,45, imbal hasil tahunan 25,57%, dan alpha 23,96%. Temuan ini mendukung kelayakan penerapan strategi factor based smart beta ETF di pasar modal Indonesia.

Kata Kunci: f*actor investing*, *smart beta*, *mean-variance optimization*, Bisnis-27, ETF, imbal hasil disesuaikan risiko

ABSTRACT

Despite the significant growth of exchange-traded funds (ETFs) in Indonesia, the ETF market share remains very low, around 1% of total mutual fund industry assets under management, as most ETF products simply replicate the index and offer limited differentiated risk-adjusted returns. This paper proposes and empirically tests a factor investing framework combined with mean-variance optimization for portfolio construction on the Bisnis-27 Index constituents. First, all 27 constituent stocks are scored and ranked using a composite multi-factor model comprising growth, quality, value, momentum, and volatility factors, standardized with z-scores and equally weighted, from which the top 15 stocks are selected. Mean-variance optimization is then applied using Solver to determine the weights that maximize the portfolio's risk-adjusted return. The portfolio is evaluated in-sample over the observation period of November 2021 to April 2025 and compared with equal-weight, factor-score, and minimum-variance weighting, as well as the Bisnis-27 Index, using the Sharpe ratio, Treynor ratio, Jensen's alpha, and information ratio. The results show that factor-selected stocks outperform the benchmark and mean-variance optimization delivers the best risk-adjusted performance with a Sharpe ratio of 1.45, an annualized return of 25.57%, and an alpha of 23.96%. The findings indicate that a factor-based smart beta ETF strategy can be implemented in the Indonesian capital market.

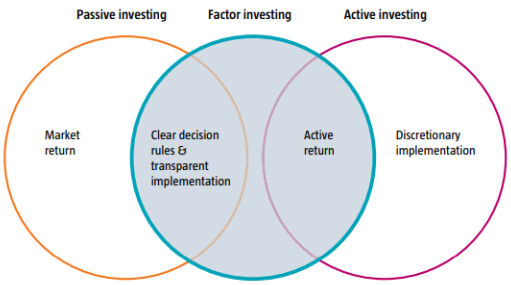
Keywords*: factor investing, smart beta, mean-variance optimization, Bisnis-27, ETF, risk-adjusted return.*

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INTRODUCTION

What drives stock returns, and is there a strategy to beat the market? This question has led to various approaches amongst academics and investors. Factor investing is often considered a middle ground between passive investing (that is, it aims to replicate the performance of a certain market index) and active investing (that is, it seeks to outperform the market performance by selecting the right assets in the markets and choosing the right sectors). Although it shares the passive characteristics of clarity, systematic rules, and low fees, as with active investing, it aims at offering returns that are better than the market. In factor investing, portfolio returns are explained by underlying factors such as quality, value, momentum, and growth (Tabot, 2023). Empirically, factor strategies have produced positive excess returns relative to the market. Morningstar data on the European, UK, and US markets indicate that factor investing (smart beta) ETFs constitute roughly 20% of a US$6.7 trillion total ETF AUM in 2022 and grew at a 14% CAGR.

Figure 1. The Concept of Factor Investing



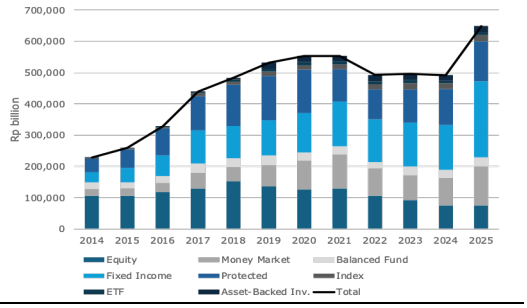
Source: MSCI, 2013

The introduction of factor investing in Indonesia provides a way to diversify portfolios and improve performance in the local ETF market, which is currently dominated by passive and active strategies with little factor investing. The Bisnis-27 is one of the best performing Indonesian indices with 27 stocks selected on fundamental and technical basis. The Bisnis-27 had a better Sharpe ratio and return compared to other comparable indices and ETFs over the period of November 2021 to April 2025.

If the Bisnis-27 index can be implemented with a semi-active factor investing strategy it will improve returns and attract more investors into the Indonesian ETF market and investors will benefit from a better risk-adjusted performance and diversification.

As of December 2025, the Indonesian mutual fund industry has a total asset under management (AUM) of Rp 689 trillion and a 9.9% CAGR since 2014 (fixed income, protected, and money market funds) whereas equity fund AUM has been declining. The reason for the decline of equity fund AUM can be found in the weak underlying returns: the Indonesian stock market grew by 2.9% CAGR from 2014 to 2025 (compared to 5.0% CAGR of fixed income products in the same period). On the other hand, ETFs and index funds have seen a surge in AUM, with ETFs increasing from Rp 1.1 trillion in 2014 to Rp 8.5 trillion in 2025 (20.2% CAGR).

Figure 2. Indonesia Mutual Fund AUM



Source: Infovesta

Despite this growth, the ETF market share is still only 1% of total industry AUM, which shows that Indonesian investors are still unaware of ETF products. A big reason for this is at the product level: Most ETF products are passive indices (like Bisnis-27, LQ45 or IDX30, etc.) and thus offer low-cost market exposure but no differentiated risk-adjusted return, which is not attractive to investors looking for more sophisticated options. Smart beta and factor investing strategies are increasingly being used in more developed

markets to bridge the gap between passive indexing and active management. However, such strategies are not widely adopted in Indonesia because factor-based portfolios are difficult to create and there is no empirical evidence in the local market.

In this paper, we propose and empirically test a two-stage factor-based portfolio construction framework for the Bisnis-27 Index. First, we screen the stocks according to a multi-factor scoring model based on growth, quality, value, momentum and low volatility. We then optimize the mean-variance of the top 15 stocks to get the best return as a percentage of risk. The portfolio is then compared to the equal-weighted, minimum-variance, factor-score and Bisnis-27 Index portfolios. The results presented in this paper should be of interest for asset managers interested in smart beta ETF development

LITERATURE REVIEW

Efficient Market Hypothesis and CAPM

The efficient market hypothesis (EMH) is the basis of many studies on stock return predictability, which states that stock prices already represent all information and follow a random walk with no excess returns over the market (Kai Yin Woo, 2020). Fama (1970) distinguishes weak-form efficiency (the prices reflect all past data), semi-strong-form efficiency (the prices reflect all public information), and strong-form efficiency (the prices reflect all information, public and private). The EMH was extended with the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) based on Markowitz's (1952) mean variance model. CAPM states that the expected return of a stock depends on the risk-free rate plus its beta multiplied by the market risk premium (Elbannan, 2015). Beta measures the sensitivity of a stock's return to market movements and stocks with beta different from 1 indicate there are other return drivers (Malkiel, 2003).

Arbitrage Pricing Theory and Factor Models

Ross (1976) proposed Arbitrage Pricing Theory (APT) to model expected returns as a function of the risk-free rate and multiple factor betas. Basu (1977) found that low price-to-earnings stocks outperform high P/E stocks, and Banz (1981) showed that small-cap firms outperform large caps. Fama and French (1992) proposed a three-factor model for market risk with size (SMB) and value (HML) factors, and Carhart (1997) added a momentum factor (WML). In addition to Jegadeesh and Titman (1993) in the winner–loser case, the case of factor investing became the empirical ground for factor investment today.

Factor Investing

Based on MSCI (2013) and Fidelity (2023), this paper is based on five factor premia. The value factor captures the outperformance of low-valuation stocks, measured by the gap between current PE, PBV, and Price-to-Sales in the past and in the current 12 months. The growth factor reflects earnings and revenue growth (1-year revenue growth and net income growth). The momentum factor, or "chasing the winners," reflects the persistence of recent return leaders (6-month price return). The quality factor seeks durable business models with strong profitability, measured by ROA, ROE, and net margin. The volatility factor represents the tendency of low-volatility stocks to have positive excess returns (Haugen, 1975) in terms of the standard deviation of daily returns.

Previous Research

Centineo and Centineo (2016) backtested global markets over 1998-2015 and demonstrated that factor-based investment yields higher risk-adjusted returns than the pure market index. Merryman and Ma (2024) compared smart beta funds with MSCI emerging market indices in five markets and Angelidis and Tessaromatis (2017) showed that factor-based country portfolios outperform the market-cap-weighted global portfolio even after transaction costs and tracking error limits.

On the size of the portfolio, classical evidence suggests that number of stocks in the range of 10-15 eliminate much firm-specific risk (Evans & Archer, 1968) and studies of emerging and less diversified markets indicate that 7-16 stocks will be meaningful diversification. Since the Bisnis-27 universe has only 27 stocks, a top-15 cutoff would be more than half the index.

RESEARCH METHOD

Data Collection

Financial statement ratios have been widely used as quantitative indicators to evaluate firm performance and investment decisions. Hidayanty and Julia (2023) have shown that accounting-based indicators like capital adequacy, liquidity, and funding factors are key to the corporate profitability of Indonesian listed banks and can be used to analyze the firm's fundamental financial data in quantitative investment. In line with this approach, in this paper, we use financial and market data from Bloomberg Terminal, Indonesia Stock Exchange (IDX), and Infovesta to develop a factor investing strategy using the Bisnis-27 Index as the investment universe. The Bisnis-27 Index comprises 27 listed companies selected by the Bisnis Indonesia Index Committee based on fundamental factors such as operating revenue, net profit, return on assets (ROA), return on equity (ROE), debt-to-equity ratio (DER), and, for banks, loan-to-deposit ratio (LDR) and capital adequacy ratio (CAR), as well as liquidity measures such as trading value, trading volume, trading frequency, trading days, and market capitalization. The selection process can also be motivated by the concept of accountability and governance, including environmental, social, and governance (ESG) and historical stock performance. The index is reviewed and rebalanced semi-annually in April and October, and constituent weights are calculated using free-float-adjusted market capitalization and a maximum weight limit of 15% for each stock.

Factor Investing Methodology

Portfolio construction follows a factor index methodology using five equally weighted factors: growth, quality, value, momentum, and volatility over the past six months).

Table 2. Multi Factor Style

Factor	Proxy
Growth	1-year Trailing 12M revenue and Trailing 12M earnings growth
Quality	ROA, ROE, Net margin
Value	Relative PE, Relative PBV, Relative P/S
Momentum	6-month price return
Volatility	Standard deviation of daily price returns over the past 6-month

Because each factor is expressed in different units, all metrics are standardized using the z-score:

$$Z = (x - \mu) / \sigma$$

where μ is the mean and σ is the standard deviation of the factor across the 27 stocks. The z-scores of the five factors are averaged into a composite total score for each stock.. Weights are capped at 15%, with excess iteratively redistributed to stocks below the cap so the portfolio sums to 100%. The top 15 stocks by composite score in each window form the portfolio.

The factor scores-based portfolio uses a rank proportional weighting methodology where the portfolio weights are assigned based on the ranking of each stock based on the composite factor sore. Consistent with the Rank Sum methodology (Alfares, 2016). Stocks with higher rankings will have bigger weights in the portfolio proportionally. The portfolio weight is calculated as:

Factor Score Weight

$$W_i = \frac{N - r_i + 1}{\sum_{j=1}^{N}(N - r_i + 1)}$$

Wi = Weight of Stock i
N = Number of Stocks in the portfolio
Ri = Ranking of the Stock

Alternative Portfolio Optimization

For comparison, we construct equal-weight, minimum-variance, and mean-variance portfolios based on Markowitz's Modern Portfolio Theory, which states that rational investors seek maximum return for a given risk or minimum risk for a given return. Unlike factor investing, these methods rely on one input, historical returns of stocks, and the risk is related to return volatility. We use the Indonesia 7-day reverse repo rate, which averaged 5.25% over the period (0.44% monthly rate) as the risk-free rate. In the equal-weight portfolio, each stock receives 1/N. Expected returns are calculated based on the average 12-month historical monthly return, and a covariance matrix is constructed using 12-month historical returns. The minimum-variance portfolio minimizes portfolio variance while the mean-variance portfolio maximizes risk-adjusted return, subject to full investment, long-only, and 15% maximum-weight constraints.:

Min-Variance: min ½ $W^T\Sigma W$
Mean-Variance: max ½ $W^T\mu$
s.t. $W^T1 = 1$, $0 \leq W \leq 15\%$

Portfolio Evaluation

Portfolio returns are evaluated on monthly actual returns. Portfolio return is the sum of stock returns and weights, and standard deviation is the return volatility. The risk-adjusted performance is evaluated with the Sharpe ratio (excess return over the risk-free rate per unit of total risk), Treynor ratio (excess return per unit of beta), Jensen's alpha (return above the CAPM-predicted return), and information ratio (active return relative to tracking error). The portfolio is measured in-sample over the observation period in semiannual rebalancing frequencies against the three alternative weightings and the Bisnis-27 Index benchmark.

Portfolio Return

$$rP = \sum_{i=1}^{k} r_i w_i$$

Standard Deviation

$$\sigma_i^P = \sqrt{\frac{\sum_{i=1}^{n}\left(r_{i,t} - \overline{r_i}\right)^2}{N-1}}$$

Sharpe Ratio

$$Sharpe\ Ratio = \frac{(r_P - r_f)}{\sigma_p}$$

Treynor Ratio

$$Treynor\ Ratio = \frac{(r_P - r_f)}{\beta_p}$$

Jensen's Alpha

$$a = Rp - [Rf + \beta \times (Rm - Rf)$$

Information Retio

$$Information\ Ratio = \frac{(r_P - r_b)}{(\sigma_P - \sigma_b)}$$

RESULT AND DISCUSSION

Factor Scoring and Stock Selection

Construction began with fundamental and market price data for the Bisnis-27 constituents. In each of the seven semiannual windows, all 27 stocks were scored on the five equally weighted factors, standardized via z-score, summed into a composite score. The top 15 stocks in each window were selected.

Table 3,			
Stocks	Nov 21-Apr 22	Stocks	May 22-Oct 22
ADRO	0.97	ADRO	0.63
PTBA	0.90	PTBA	0.54
EMTK	0.36	MDKA	0.40
MIKA	0.22	UNVR	0.32
MDKA	0.22	BBCA	0.25
ICBP	0.17	INDF	0.22
BBRI	0.10	KLBF	0.20
BBCA	0.10	INKP	0.15
BMRI	0.08	UNTR	0.10
UNTR	0.08	BMRI	0.10
KLBF	0.07	PGAS	0.04
PWON	0.06	TLKM	0.02
TLKM	0.05	BBRI	0.02
TPIA	0.00	AMRT	-0.01
ASII	-0.01	CPIN	-0.04

Table 4,			
Stocks	Nov 22-Apr 23	Stocks	May 23-Oct 23
BBCA	0.42	BBCA	0.74
ESSA	0.40	ICBP	0.49
ADRO	0.39	BBRI	0.30
BBRI	0.38	JSMR	0.29
INDF	0.35	BBNI	0.22
UNVR	0.33	BMRI	0.21
PTBA	0.29	ANTM	0.21
ASII	0.22	ITMG	0.19
TOWR	0.21	MAPI	0.16
BBNI	0.15	UNVR	0.14
ANTM	0.15	INCO	0.04
MDKA	0.10	TLKM	-0.07
UNTR	0.06	MTEL	-0.08
INCO	0.03	AMRT	-0.08
TLKM	-0.06	INTP	-0.08

Table 5.			
Stocks	Nov 23-Apr 24	Stocks	May 24-Oct 24
BBCA	0.88	ADRO	1.52
BMRI	0.67	BBCA	0.71
JSMR	0.56	JSMR	0.64
BBRI	0.30	AMRT	0.53
TLKM	0.29	KLBF	0.41
BBNI	0.27	MYOR	0.39
ASII	0.20	UNTR	0.32
UNTR	0.17	BMRI	0.18
AMRT	0.17	BBRI	0.18
PGAS	0.13	MIKA	0.15
MIKA	0.08	ICBP	0.12
ISAT	0.02	CTRA	0.12
MTEL	-0.02	PGAS	0.08
AKRA	-0.04	BBNI	0.06
ADRO	-0.07	ASII	0.05

Table 5.	
Stocks	Nov 24-Apr 25
ANTM	0.00
BBCA	0.01
MIKA	0.24
PTBA	0.00
PGAS	0.01
ICBP	0.21
CPIN	0.00
ASII	0.08
MYOR	0.13
UNTR	0.06
ADMR	0.05
BRIS	0.01
KLBF	0.01
TLKM	0.01
MEDC	0.01

In the first two windows (November 2021 to October 2022), energy and commodity names such as ADRO and PTBA dominated on the back of strong commodity-boom earnings.
From November 2022 to April 2023, leadership shifted toward large-cap banks (BBCA, BBRI, BMRI) and consumer/infrastructure names (ICBP, JSMR, TLKM) as commodity earnings slowed.

In the final window (November 2024 to April 2025), the model favored a defensive mix of resilient, low-valuation names such as ANTM, BBCA, MIKA, and PTBA. No single factor dominated selection across the period, confirming the diversification benefit of the equally weighted multi-factor approach as leadership migrated from growth and momentum toward quality, value, and low volatility.

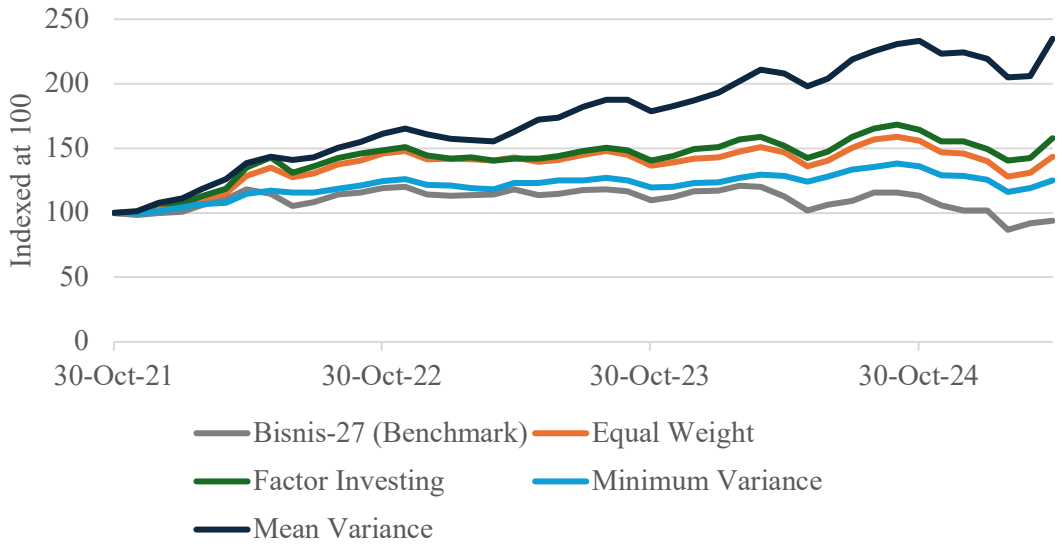
Mean-Variance Optimization

In the second stage, mean-variance optimization was applied to the 15 selected stocks, with expected returns from the average 12-month monthly return, risk from the return standard deviation, and a 15×15 covariance matrix from 12-month monthly returns. The optimization maximized risk-adjusted return subject to full investment, long-only, and 15% maximum-weight constraints. For comparison, the same 15 stocks were also weighted by equal weight, factor score, and minimum variance.

Portfolio Performance

Applying each method's weights to actual monthly returns, with a 5.25% annual (0.44% monthly) risk-free rate, produces the performance summary in Table 1. Factor investing with mean-variance optimization delivers the highest return, followed by factor-score weighting, equal weight, and minimum variance, with all methods outperforming the Bisnis-27 benchmark.

Figure 3. Indonesia Mutual Fund AUM



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Table 6. Portfolio Performance Summary (November 2021-April 2025)

Metric	Bisnis-27 (Benchmark)	Equal Weight	Factor Investing	Min. Variance	Mean Variance
Mean monthly return	(0.04%)	0.95%	1.19%	0.57%	2.13%
Annualized return (arithmetic)	(0.53%)	11.44%	14.33%	6.89%	25.57%
Monthly std dev	4.58%	4.27%	4.55%	2.79%	4.04%
Annualized std dev	15.88%	14.80%	15.76%	9.68%	13.99%
Beta	1.00	0.79	0.77	0.49	0.63
Risk-Adjusted Performance					
Sharpe ratio (annualized)	-0.36	0.42	0.58	0.17	1.45
Treynor ratio (annualized)	-5.78%	7.86%	11.74%	3.32%	32.32%
Jensen's alpha (annualized)	0.00%	10.75%	13.55%	4.49%	23.96%
Information ratio (annualized)	-	1.39	1.41	0.75	2.28

Risk-Adjusted Performance

The benchmark's negative Sharpe ratio of -0.36 indicates that the Bisnis-27 failed to compensate investors even for the risk-free rate. Of all the portfolios developed, mean-variance optimization achieved the highest Sharpe ratio of 1.45, compared to 0.58 for actor-score weighting, 0.42 for equal weight and 0.17 for minimum variance, indicating the value added by the second stage optimization.

The Treynor ratio ranking is identical, where mean-variance is 32.32%, with a low beta of 0.63 which indicates that positive Jensen's alpha is obtained with limited market exposure: this means that the excess returns can be attributed to first-stage factor selection rather than market exposure. All methods produced positive Jensen's alpha, 23.96% for mean-variance, which indicates that the excess returns arise from factor selection than due to market-risk exposure.

Finally, the information ratio (2.28 for mean variance) shows the best outperformance in the benchmark and lowest minimum variance (0.75) as its deviation from the benchmark is large compared to the active return..

CONCLUSION & RECOMMENDATION

This study shows that factor investing can be implemented systematically on the Bisnis-27 Index constituents. A composite multi-factor model scores all 27 stocks on growth, quality, value, momentum, and volatility, standardized with z-scores and equally weighted, and selects the top 15 stocks as the investment universe. The factor-based mean-variance portfolio outperforms the equal-weight, minimum-variance and Bisnis-27 benchmark portfolio risk-adjusted by the same margin for Sharpe ratio, Treynor ratio, Jensen's alpha and information ratio. The mean-variance optimization strategy has a Sharpe ratio of 1.45, the alpha of 23.96% and information ratio of 2.28. The two stages are complementary: the first stage makes the universe better than the index for every weighting process and the second stage makes the risk-adjusted return of the selected stocks better. These findings also confirm the feasibility of a factor-based smart beta ETF product in Indonesia with the systematic rules, transparency, liquidity-aware weighting, and index-consistent constraints investors and regulators require and have led to the differentiation gap which has kept ETF market share to a fraction of industry AUM.

For asset managers, the framework we tested provides a good starting point for smart beta ETF development, with its transparent factor-scoring and mean-variance optimization as a weight-refinement. For investors, the results suggest that the rules-based semi-active product can deliver better risk-adjusted results than passive index tracking, but should be evaluated over a full market cycle as factor leadership fluctuates. Future research could use out-of-sample backtesting, extend the horizon to cover a full market cycle to include transaction costs and rebalancing frequency to estimate net performance and test other factor weightings or a broader universe, such as the IDX80 or Kompas100 Index.

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