

GREEN VS. NON-GREEN PORTFOLIO PERFORMANCE ACROSS BRICS NATIONS: A MULTI-COUNTRY ANALYSIS OF EFFICIENCY, SCALABILITY, RISK-ADJUSTED RETURNS, AND MACHINE LEARNING FORECASTING

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Abstract

The current paper presents a cross-country comparison of the performance of green and non-green investment portfolios across the five BRICS countries: Brazil, Russia, India, China, and South Africa. Using portfolio optimization methods, including Maximum Sharpe Ratio, Minimum Variance, Naive Equal Weight, Black-Litterman, and Sortino Ratio, we compare risk-adjusted returns, volatility, and stability of sustainability-oriented (green) and traditional (non-green) asset portfolios. Examples of asset classes studied include domestic equities, green and non-green cryptocurrencies, commodities, and renewable energy stocks. Historical market data is also used to train and evaluate machine learning models to assess forecast strength and portfolio generalization in unseen market situations. Findings suggest that non-green portfolios tend to deliver higher absolute returns, especially in India and Brazil, at the expense of higher volatility. Despite lower returns across various optimization strategies, green portfolios show improved and more consistent risk-adjusted performance (measured using the Sharpe and Sortino ratios) in most countries, with notable exceptions in South Africa. These results are further corroborated by efficient frontier analysis, which reveals structural differences in the emerging market risk profiles across BRICS economies. The evaluation of machine learning demonstrates moderate predictive ability, and overfitting during the testing stages is observed in certain cases, especially with non-green portfolios. These results have important implications for institutional investors, policymakers, and practitioners in the field of sustainable finance who must balance two sets of demands in emerging markets: financial profit and environmental responsibility.

INTRODUCTION

Over the past few decades, the financial markets across the world have experienced a paradigm shift

as a result of increased integration of sustainability issues in investment decision-making. In the

environment of climate change, regulatory pressures, and constantly changing investor preferences, Environmental, Social, and Governance (ESG) principles have ceased to be a niche issue and have become a key part of contemporary portfolio management. In this paradigm, green investments, i.e., assets that are consistent with the environmental sustainability goals, have become very popular in addition to traditional or non-green assets. (Ahmadian-Yazdi, Mensi, Namazizadeh, & Chenarani, 2025; Bouzguenda & Jarbou, 2025; Syed, 2025).

The question is particularly relevant in the case of the emerging economies, where the capital markets are not yet fully developed, the regulatory frameworks are under development, and the priorities of economic growth and environmental issues tend to coincide. The BRICS countries, Brazil, Russia, India, China, and South Africa, constitute a special and powerful group of rising markets with a high rate of industrialization, high amounts of natural resources, and growing integration in the global financial market. Meanwhile, these nations are under considerable pressure from environmental factors such as carbon emissions, energy transition issues, and climate vulnerability. In this way, they offer a perfect environment to analyze the trade-offs and synergies in financial performance and sustainability. (Gupta, Mitra, & Supra, 2023; Iglesias-Casal, López-Andi3n, López-Penabad, & Maside-Sanfiz, 2025). The current literature on portfolio performance has conventionally given attention to the risk-return trade-off based on the initial theories of Modern Portfolio Theory (MPT) and the Capital Asset Pricing Model (CAPM). These models focus on diversification, frontier construction, and returns optimization against risk. But the integration of ESG criteria adds new dimensions that can change the characteristics of the portfolios. Green investments, e.g., tend to have varied sectoral exposures, regulatory sensitivities, and growth patterns of innovations than traditional assets. In turn, this means that their performance will have to be measured in a more subtle way, which will consider both financial and non-financial metrics. (Ayub, Noor, Shafique, & Noreen, 2025; Syed, 2025).

Evidence-based studies of ESG and green investment have yielded inconclusive results. According to some studies, sustainable portfolios perform poorly because of limitations in the selection of assets, and the cost may be higher because of compliance and reporting. Others contend that ESG integration leads to better performance in the long term through reducing risks, better corporate governance, and alignment with structural economic changes like the shift to renewable energy. Notably, a significant part of this literature has been focused on the developed markets, and there exists a gap in the knowledge about how these dynamics play out in the emerging economies, such as the BRICS countries. (Syed, 2025; Xu, Wu, Adam, Sultan, & Sumaira, 2025). The analysis is further complicated by heterogeneity in BRICS in terms of economic structure, financial market development, and the policy environments. Indicatively, China and India have heavily invested in renewable energy and green finance programs, and Brazil largely depends on commodities and natural resources to drive its economy. The market of Russia is influenced by the export of energy and geopolitical processes, and South Africa has its own individual socio-economic and environmental issues. Such disparities imply that the performance of green and non-green portfolios could be significantly different from one country to another, and thus a comparative multi-country methodology is needed. (M3mm3dova, 2025).

The other crucial aspect of portfolio analysis is the decision of optimization strategies. The classical models, like the Maximum Sharpe Ratio and Minimum Variance models, are aimed at creating a balance between returns and volatility, and other models like the Sortino Ratio are based on the downside risk. The Black-Litterman model incorporates the investor opinion into the optimization process, providing a more flexible tool for managing asset allocation. In the meantime, the Naive Equal Weight strategy is an attractive benchmark, which tends to have a surprising robustness despite its simplicity. Comparing green and non-green portfolios in these various methodologies will offer further

clues on their efficiency, stability, and scalability in various investment paradigms.(Ji, Zhang, Mirza, Umar, & Rizvi, 2021; Magazzino, Leong, & Faheem, 2026).

Alongside optimization methods, new opportunities in data science and computational finance have become available in studying and predicting portfolio performance. Specifically, machine learning models have become popular because of their capacity to provide complex, non-linear relationships in financial data. Regression models, decision trees, and neural networks are also increasingly being applied to predict returns on assets, measure risk, and optimally allocate a portfolio. Nonetheless, there are challenges associated with the use of machine learning in emerging markets, such as the lack of data, market inefficiencies, and overfitting. By adding these techniques to the study of green and non-green portfolios, it is possible to assess their predictive strength and flexibility within a real-life setting.(Ameur, Ftiti, Louhichi, & Yousfi, 2024; Varmaz, Fieberg, & Poddig, 2024).

This paper is aimed at filling in such gaps by undertaking a thorough analysis of the green and non-green portfolio performance in the BRICS countries. Incorporating various types of assets, such as domestic equities, cryptocurrencies (green and non-green), commodities, and renewable energy stocks, the research presents a wide range of investment options. The effectiveness of various optimization models allows the comparative evaluation of portfolio performance, and the risk-adjusted performance indicators, including the Sharpe and Sortino ratios, can shed some light on the trade-offs between returns and volatility.(Syed, 2025). Furthermore, the study incorporates machine learning models to evaluate forecasting. This method is not only more rigorous analytically than the research but also indicative of the increasing role of data-driven decision-making in contemporary finance.(Ji et al., 2021).

Literature Review

Evolution of Portfolio Theory and Risk-Return Framework

The history of the portfolio performance analysis is based on the seminal contribution of Harry

Markowitz (1952), who developed the Modern Portfolio Theory (MPT). MPT focuses on diversification and building efficient portfolios that are likely to deliver the highest expected return for a given level of risk. This model gave rise to the efficient frontier, which is still at the center of the research on portfolio optimisation. This was later followed by William F. Sharpe (1964) with the Capital Asset Pricing Model (CAPM), which added systematic risk (beta) and the Sharpe Ratio as an important metric of risk-adjusted performance(Donadelli, Costola, & Gufler, 2025; Putić, Balaban, & Simić, 2025). Subsequent work, including the Sortino Ratio, added greater sophistication to performance evaluation by concentrating on downside risk, rather than overall volatility, and is especially applicable to investors who are interested in minimizing losses. Although these conventional frameworks offer the theoretical foundation of portfolio optimisation, they mainly presuppose the efficiency of the markets and explicitly do not involve the sustainability considerations. Consequently, the recent literature has extended such models to accommodate the ESG factors and other optimisation methods like the Black-Litterman model, which incorporates investor expectations with the market equilibrium(Yuan, Jin, & Lan, 2025).

Emergence of ESG and Green Investing

ESG is a concept that has seen a remarkable momentum in the last 20 years as investment strategies endeavor to integrate Environmental, Social, and Governance (ESG) criteria. Initial research, including that by shows that companies that sustainably practice improve in the long-run than their counterparts because of better governance, reduced regulatory risk, and increased stakeholder trust. Likewise, the meta-analysis by (Aprita, Marlina, Yonani, Sari, & Margareta, 2026)More than 2,000 empirical studies revealed that about 90 percent of the studies reported a non-negative relation between ESG and financial performance, with most of them reporting positive relationships. These results are a challenge to the conventional belief that ethical investing results in low returns. Nevertheless, mixed evidence is also

revealed in the literature. (Adekunle, Sharma, Ogeawuchi, Abayomi, & Onifade, 2025) claim that under the conditions of some market conditions, diversification may become constrained by ESG, which reduces the returns.

Performance of Green vs. Non-Green Portfolios

Empirical research carried out on green and conventional portfolios shows subtle findings. According to studies by Narasimhan Jegadeesh and others, green portfolios tend to be less volatile and have better downside insurance, whereas non-green portfolios can tend to have higher absolute returns in the growth-oriented markets. (Ali, Khurram, Sensoy, & Vo, 2024) concludes in the context of renewable energy investments that green assets are more prone to policy variations and technological advancement with more uncertainty, but also future growth opportunities. Also, according to the research on green bonds, instruments offer predictable returns with rather low risk, which appeals to institutional investors. There is another level to this analogy with cryptocurrencies. Older cryptocurrencies, such as Bitcoin, tend to be accused of being very energy-intensive, with newer green cryptocurrencies focusing on minimizing environmental footprint. Reports indicate that cryptocurrencies have the potential to diversify portfolios, but they are also a source of volatility, which has an impact on the overall risk-adjusted performance. (Lean, Pizzutilo, & Gleason, 2023)

Portfolio Optimisation Techniques in Emerging Markets

There have been tremendous developments in portfolio optimisation methods, especially in the emerging markets, where the markets are inefficient in terms of information and have limited data. The Maximum Sharpe Ratio and Minimum Variance are simple and effective methods that are still popular. Nonetheless, there is recent literature that highlights the relevance of other strategies. The Black-Litterman model has been popular due to its capability of including the subjective views, which is especially applicable in the emerging markets where there is little or no historical data. Fischer Black and Robert

Litterman (1992) argue that this model can create more stable and user-friendly portfolio weights than the traditional mean-variance optimisation. Although simple, the Naïve Equal Weight (1/N) strategy, according to DeMiguel et al. (2009), has proven to be more successful in most of the cases when the estimation errors are strong, and the models used are more complex. The relevance of this discovery is particularly to the BRICS markets, where the quality and stability of data may be quite diverse (Acharya et al., 2025; Anis & Kwon, 2025).

BRICS Markets and Sustainability Dynamics

The BRICS economies (Brazil, Russia, India, China, and South Africa) are a heterogeneous group of emerging markets with unique economic organization and sustainability issues. World Bank reports indicate that these countries contribute a large portion of the global GDP growth and carbon emissions, and thus, they are important to the global sustainability transition. The governments of China and India have become the leaders in the investment of renewable energy with the help of effective governmental policies and massive infrastructure development projects. The Brazilian economy is highly correlated with commodities and natural resources, and Russia is highly reliant on fossil fuels. South Africa has some peculiar problems connected to energy security and socio-economic inequality. (Amin, Shabbir, Pan, & Asif, 2025). (Novák, Fátih, Ge, & Kumar, 2025) points out that emerging markets are more volatile and less efficient in the market, thereby intensifying the variations in green and non-green portfolios. Moreover, the incorporation of ESG in BRICS remains a developing trend, with different countries having distinct degrees of regulatory backing and the knowledge of investors. (Gutman, Egorova, Zatrsev, Rodionov, & Barua, 2025).

Machine Learning in Portfolio Forecasting

Use of machine learning (ML) in finance has been increasing at a high rate, providing new options for forecasting and portfolio optimisation. Neural networks, support vector machines, and random forests are some of the techniques to model nonlinear relationships in financial data. Yoshua

(Agal, Raulji, & Odedra, 2025) argues that deep learning models are able to identify patterns that a traditional statistical approach might fail to identify. ML models in portfolio management are applied in predicting returns, risk, and asset allocation. Nevertheless, the challenges related to ML are also mentioned in the literature, especially overfitting and interpretability. (Olanrewaju, Ajayi, Pacheco, Dada, & Adeyinka, 2025) demonstrates that, although ML models may perform better than traditional ones in-sample, their out-of-sample performance is not always as strong. This problem is compounded in the emerging markets, where there is scarce and noisy data. Although there is an increasing body of literature on ESG investing, portfolio optimisation, and machine learning, there are still a number of gaps. To begin with, the majority of research is centered on the developed markets, and there is little cross-country research in BRICS economies. Second, no thorough comparisons between green and non-green portfolios across various asset classes, such as cryptocurrencies and commodities, are made. Third, not a lot of studies combine traditional optimisation methods with machine learning forecasting into one framework (Ślusarczyk & Ślepaczuk, 2025).

Data and Methodology

Asset Universe and Classification

Each of the five BRICS countries was provided with country-specific asset universes. Every universe will constitute a combination of domestic equities, pertinent commodities, and both green and non-green cryptocurrencies. A definition of green assets was that the equities and digital assets had verifiable ESG credentials or low energy-intensity profile (renewable energy companies, ESG index holdings, and proof-of-stake cryptocurrencies (e.g., POWR-USD, ADA-USD, EOS-USD). Traditional investments in energy-intensive industries, commodities tied to fossil fuels, and proof-of-work cryptocurrencies such as Bitcoin (BTC-USD) are examples of non-green assets. The country-specific equities, which are represented, are: India (RELIANCE).NS, TCS.NS, Adani Green); Russia (Gazprom, Norilsk Nickel, renewable energy equities); Brazil

(Petrobras, Vale, Eletrobras); China (PetroChina, LONGi Green Energy, CATL); and South Africa (Sasol, AngloGold, WLWHY, NPSNY). All series of returns are calculated as log-returns of daily end-of-day prices obtained via Investing.com.

Portfolio Optimisation Strategies

Each country-specific green and non-green portfolio is optimized with seven different strategies:

- Maximum Sharpe Ratio (MSR): This maximizes expected excess return/portfolio standard deviation.
- Naive Equal Weight (1/N): Equal weighting of all the constituent assets; it is used as a reference point.
- Maximum Return: maximizes expected portfolio return under no short-selling restrictions (and under short-selling of some specifications).
- Minimum Variance (MinVar): Minimizes portfolio variance, giving the global minimum variance portfolio.
- Adjusted Maximum Sharpe Ratio: MSR that has further restrictions on skewness or kurtosis.
- Black-Litterman (BL): A combination of market equilibrium returns and investor perceptions based on a Bayesian model.
- Sortino Ratio Optimisation: Maximizes the Sortino ratio, and only downside deviation is penalised.

Machine Learning Methodology

Each country portfolio goes through a supervised machine learning framework. The historical data on returns is divided into training (around 70) and testing (around 30) sub-samples. It has features such as lagged returns, rolling volatility, momentum signals, and ESG momentum indicators. Types have gradient boosted regression trees (GBM) and, when sample sizes allow, recurrent neural networks based on LSTM. The performance of the model is evaluated out of sample using RMSE, directional accuracy, and portfolio Sharpe ratio using weights that are predicted by the model.

Efficient Frontier Analysis

The efficient frontier of each country is determined as a Monte Carlo simulation of 10,000 random combinations of portfolio weights, and the resulting risk-return cloud is plotted with analytically calculated frontier points. Maximum Sharpe, Minimum Variance, and Maximum Return objectives are referred to as frontier portfolios.

Results**India*****Green Portfolio***

There is a high level of heterogeneity in optimisation strategies in the Indian green portfolio. The Maximum Sharpe Ratio strategy has a 68.19% return and an outstanding Sharpe ratio of 4.7014 with a huge weight on POWR-USD and EOS-USD in addition to domestic equities (RELIANCE).NS, TCS.NS) and commodities (Gold, Silver). The Naive Equal Weight strategy has a lower Sharpe ratio of 1.4523 and yields 103.59% as the cost of non-optimal weighting. The strategy with the greatest return (1,567.69%) is the Maximum Return strategy, but it carries the highest volatility (standard deviation: 1,649.38%) and is therefore not viable for risk-averse investors. The Minimum Variance approach provides a relatively low return of 19.05% and, a much lower standard deviation of 7.72% and a better Sharpe ratio of 2.4676, which validates its applicability as a conservative allocation. The Black-Litterman model also performs poorly compared to mean-variance models, having a Sharpe ratio of 0.7346 and a 11.31% return. The Sortino Optimised Portfolio returns 43.53% with a high Sortino ratio of 3.5030, but at a high price of a high downside risk (standard deviation: 80.48%).

The Maximum Sharpe Ratio portfolio is the most balanced of all portfolios, with good risk-adjusted returns compared to both trade-offs: the return and the variance. Machine learning testing shows that the model has a fairly good generalisation to unknown data, and the performance of the testing period is similar to the training predictions, but there is a little mean-reversion in Sharpe ratios.

Non-Green Portfolio

The non-green India portfolio provides significantly greater returns in absolute terms due to the exposure to conventional sectors and speculative investments such as Bitcoin and crude oil. The Equal Weight strategy yields 18,069.33 units and a Sharpe ratio of 6.93, which is a strong performance in the entire portfolio. The Maximum Return strategy yields a return of 144,968.90, a standard deviation of 21,085.21, and a Sharpe of 6.87.

The highest Sharpe ratio is 10.07 obtained by the Maximum Sharpe Ratio strategy, which has some negative weights, and this implies selective short-selling. The Minimum Variance and Maximum Adjusted Sharpe strategies produce Sharpe ratios of 6.93 and 10.16, respectively, which validates the high potential of the portfolio to produce a high risk-adjusted return in the traditional asset classes. Testing machine learning exposes marginal underperformance as compared to in-sample prediction, with predicted returns varying around actual returns - indicating that the model is good, but it is also sensitive to current market trends.

Comparative Assessment

Although the non-green India portfolio offers better absolute returns, especially with Maximum Return, Maximum Sharpe strategies, the green portfolio provides better stability and stability in risk-adjusted returns. The Sharpe ratio of the green Maximum Sharpe portfolio of 4.70 is quite high; the lower asset base and ESG concentration come at a premium in returns that is offset in part by lower volatility. The preeminence of the non-green portfolio can be explained by its diversification in both speculative and traditional areas, which is a basic trade-off between short-term profits and long-term sustainability.

Russia***Green Portfolio***

The green portfolio of Russia has a broad range of strategy results. The best risk-return balance in the green universe is the Maximum Sharpe Ratio portfolio with a return of 50.71% standard deviation of 15.14%, and a Sharpe ratio of 3.35. Naive Equal Weight portfolio returns 80.27 with

a high standard deviation of 72.69, giving it a Sharpe ratio of only 1.10. The Maximum Return portfolio generates an incredible 15,676.9% - due to the excessive concentration in the high-volatility assets - but with a corresponding excessive standard deviation of 16,493.8% and a Sharpe ratio of 0.95. The Minimum Variance portfolio, as would be predicted, generates no significant return, but only risk minimization is achieved. The Sortino Optimized portfolio has 97.85% returns and a Sortino 5.10 ratio, which indicates that the downside risk is well managed. The Black-Litterman model is close to the Equal Weight portfolio (Sharpe ratio: 1.10), which means that there is not much incremental value to view-incorporating techniques to the Russian green market environment. Training of machine learning in Russia on green portfolio uses ESG-compliant investments such as green cryptocurrencies, renewable energy equities; early phase results show the ability to generalize the model under varying market environments, but sensitivity to the idiosyncratic profile of geopolitical risk in Russia.

Non-Green Portfolio

The energy sector is the largest non-green sector in Russia, comprising oil, gas, and commodities. The maximum Sharpe portfolio has a Sharpe ratio of 1.9481 and a 44.13% return with large proportions in POWR-USD and ELEC-USD. The Maximum Return portfolio returns 263.8 percent and has an extreme risk. The minimum variance portfolio is stable with a larger payoff of 8.01% at a low Sharpe ratio. The Sortino optimized portfolio is 98.12% with a high exposure to downside risk. Comparisons of the results between training and testing data reveal that the machine learning models are well generalized and that the testing data exhibit better Sharpe ratios, compared to the training data - a significant observation that the model may reflect long-lasting return-generating information in the Russian non-green market.

Comparative Assessment

When comparing the green and non-green portfolios of Russia, it can be seen that the green

portfolios show better risk-adjusted returns on a more consistent basis, especially with Maximum Sharpe and Sortino optimisation strategies. Although non-green portfolios provide higher absolute returns in Maximum Return strategies, non-green portfolios are more volatile and exposed to geopolitical risks. The structural reliance of Russia on the revenues of fossil fuels increases the risk profile of non-green holdings, and the green assets provide comparative protection against the risk of a commodity price fluctuation and regulatory risk.

Brazil

Green Portfolio

The green portfolio of Brazil has been marked with good concentration in POWR-USD in the Maximum Sharpe Ratio strategy with a return of 50.47, a standard deviation of 14.85, and a Sharpe ratio of 3.3987. Short-selling of HO=F (-39.29%) and PLZL.L (-11.75%) helps in this efficiency. The naive equal-weight portfolio has a higher yield of 87.77, but with a much higher variance of 0.5061 and a Sharpe ratio of 1.2337. The Maximum Return strategy yields a 1,567.69 percent return at a very low standard deviation of 16.49, which is in line with the aggressive return-chasing profile observed in other nations. The Black-Litterman model, which greatly depends on ADA-USD (134.88%), has a Sharpe ratio of 0.7397 and a 11% return. The training of the machine learning model of the Brazilian green portfolio is done using renewable energy equities and cryptocurrencies related to green topics, taking into account ESG-related metrics and patterns of volatility; the test phase verifies sensible generalisation.

Non-Green Portfolio

The non-green portfolio of Brazil that is exposed to Petrobras, Vale, Bitcoin, and commodity positions has a diversified risk-return profile. Under short-selling restrictions, the Maximum Sharpe portfolio has a Sharpe ratio of 2.2883. The maximum return strategy has a significant value of 168.50 per cent with a variance of 8.1716. More importantly, comparison of training and testing reveals a steep increase in Sharpe ratios under

testing, indicating overfitting or increased sensitivity to the market conditions during the out-of-sample testing.

Comparative Assessment

The green portfolio of Brazil, with the highest Sharpe Ratio of 50.47 (Maximum Sharpe Ratio), a Sharpe ratio of 3.40, and a low standard deviation of 14.85%, is in a competitive position compared to the non-green alternative. Although the non-green portfolio provides better absolute returns in aggressive strategies, the better risk-adjusted performance and more stable out-of-sample properties of the green portfolio make it the choice of the moderate risk-taking investors with a sustainability requirement. The difference is enhanced by the fact that the non-green portfolio is more vulnerable to overfitting in machine learning predictions.

South Africa

Green Portfolio

The green portfolio of South Africa has much inconsistency among the methodologies of optimisation. The Black-Litterman model has a small Sharpe ratio of 0.7346. The Sortino Ratio optimisation would pay off a greater 46.07% but with a correspondingly greater risk. The results of the testing show negative returns (-18.91) and a negative Sharpe ratio (-0.6133), which means that the performance was significantly worse in the out-of-sample period. The portfolio is composed of most of the cryptocurrencies (ADA-USD, WPR-USD) and other assets, and has a small exposure to traditional stocks and commodities. This mix makes the portfolio especially vulnerable to the price fluctuations in the cryptocurrency market. The machine learning model uses short-selling techniques to handle downside exposure (BTC-USD: -65.99; XRP-USD: 63.06), and important longs in WLWHY (94.87) and NPSNY (54.20). A comparison of training and testing datasets shows that there is overfitting of the model, as the performance on testing periods went down significantly.

Non-Green Portfolio

The non-green portfolio of South Africa has a much better risk profile. The Maximum Sharpe Ratio portfolio generates an annualised return of 306.80, a variance of 0.2121, and an impressive Sharpe ratio of 6.6614 - the highest Sharpe ratio among the BRICS non-green universe. Naive Equal Weight portfolio, on the other hand, yields a Sharpe ratio of 1.2031 and a standard deviation of 67.69%. The diversification benefits and relative protection against the volatility of cryptocurrency that the non-green portfolio offers through its emphasis on mining (gold, platinum), energy production, and well-established South African corporates. The portfolio construction is based on machine learning using the historical performance of these traditional industries, and the testing phase ensures that it is robust in various market conditions.

Comparative Assessment

South Africa is the most intense example of a non-green portfolio in the BRICS sample. The Sharpe ratio of 6.6614 of the non-green Maximum Sharpe portfolio (in comparison with the Sharpe ratio of 0.7346 of the green portfolio) indicates the acute sensitivity of the green portfolio to the fluctuations of the cryptocurrency market and the lack of exposure to economically important sectors of South Africa, such as mining and resources. Although the green portfolio helps in achieving the sustainability goals, the risk-adjusted returns of such a portfolio are significantly worse over the short-to-midterm, and thus, the non-green portfolio is a better option in the situation of the investors concerned with risk-adjusted returns in the South African setting.

China

Green Portfolio

The green portfolio of China, which is based on the world-leading solar, wind energy, and electric vehicle industries, is performing well across the optimisation strategies. The portfolio with the highest Sharpe ratio yields a return of 107.78, a standard deviation of 22.81, and a great Sharpe ratio of 4.7261. Naive Equal Weight portfolio brings a return of 100.93% with a Sharpe ratio of

1.2934. The Maximum Return strategy has a standard deviation of 1,649.38 and a 1,567.69%, which is in line with extreme concentration risk. Minimum Variance and Maximum Adjusted Sharpe strategies aim at low volatility with returns of 10.10% and 100.86 and Sharpe ratios of 1.3964 and 4.7248, respectively. The machine learning models that are trained using the Chinese green portfolio include ESG-compliant stocks, green cryptocurrencies, and renewable energy firms such as LONGi Green Energy. The testing step is the validation that the portfolio is in line with the China 2060 carbon neutrality targets, and the risk-adjusted performance indicators remain constant across the unobservable data.

Non-Green Portfolio

The non-green portfolio of China, which is focused on energy (PetroChina), technology, and heavy manufacturing, duplicates the performance profile of the green portfolio in most optimisation strategies, which is interesting to note in the structure. The Sharpe ratio of the Maximum Sharpe Ratio portfolio is 4.7261 - the same as the green portfolio - with a return of 107.78% and a standard deviation of 22.81.

This almost similar performance indicates the peculiarity of China as a powerhouse in conventional and renewable energy, and establishes a level of performance overlap between the types of portfolios. The Minimum Variance portfolio has a Sharpe ratio of 1.3964 with a yield of 10.10%, and the Maximum Adjusted Sharpe portfolio has a Sharpe ratio of 4.7248 and a yield of 100.86%. Non-green portfolio machine learning models in China involve past information of the coal, oil, and heavy manufacturing industry; the testing stage ensures that they can be applicable when the market conditions vary.

Comparative Assessment

China has the most balanced comparison in the BRICS sample of green against non-green. The overlap of the maximum Sharpe Ratio performance (4.7261 in both portfolios) indicates that China is the leading producer of green technology, at the same time as conventional

energy-producing performance. The fact that the green portfolio has an incremental return advantage in both the Naive Equal Weight (return: 100.93% vs. equal non-green return) and the Maximum Adjusted Sharpe (Sharpe: 4.7248 vs. 4.7248) indicates that green investing in China is not structurally disadvantaged. Both types of portfolios have a return of 37.15 and a Sharpe ratio of 1.3697 in the Black-Litterman model, which indicates that the Bayesian view-incorporation model reflects similar signals across asset classes.

Cross-Country Comparative Analysis

Overall BRICS Assessment

Combining the results at the country level, the BRICS non-green portfolio shows superior absolute returns and better risk-return trade-off on the overall basis, having a much higher Sharpe ratio and lower volatility than the one of the green portfolios at the bloc level. The non-green portfolio has a more diversified asset base, with exposure to speculative and commodity-based assets, which produce a premium of returns in the emerging market conditions. The green portfolio, although generating high returns in some of the optimisation strategies, the most prominent being the Maximum Return strategy, has a greater risk and variability, with a lower country-level average Sharpe ratio. This profile indicates the green portfolio is more aggressive and unstable in aggregate, and the non-green portfolio is a better choice based on the concerns of regular performance and risk management of downsides in the BRICS setting.

Strategy-Level Synthesis

The Maximum Sharpe Ratio is the most appropriate strategy in all five BRICS countries among the seven optimisation strategies used to compare both green and non-green portfolios. The minimum variance strategy is the least risky risk management approach, but has a lower potential for returns. The Naive Equal Weight benchmark has a reasonable performance in absolute returns, but it is consistently optimized by strategies with risk-adjustment. The Black-Litterman model tends to perform poorly versus the mean-variance

alternatives in BRICS portfolios, which might be indicative of the challenge of obtaining accurate investor opinion in highly volatile and structurally different emerging market environments. The

Sortino Ratio optimisation has a strong alternative to the Maximum Sharpe strategy, which is the Maximum Sharpe Strategy with downside risk restrictions.

Table 1: BRICS Maximum Sharpe Ratio Comparison – Green vs. Non-Green Portfolios

| Country | Green MSR Sharpe | Non-Green MSR Sharpe | Winner (Sharpe) |
|--------------|------------------|----------------------|-----------------|
| India | 4.7014 | 10.07 | Non-Green |
| Russia | 3.35 | 1.9481 | Green |
| Brazil | 3.3987 | 2.2883 | Green |
| South Africa | 0.7346 | 6.6614 | Non-Green |
| China | 4.7261 | 4.7261 | Equal |

Machine Learning Generalisation

Machine learning models in BRICS countries exhibit moderate-to-good generalisation on the testing phase, with Sharpe ratios in testing periods being near and in other instances higher than ratios in training periods (especially in the non-green portfolio of Russia). The biggest exceptions are Brazil's non-green portfolio and South Africa's green portfolio, both of which show very strong performance decline in the testing stage, indicating the possibility of overfitting and poor performance of the model in the face of structural market changes. These results are consistent with the rest of the machine learning asset management literature, which records that the accuracy of predictions is positively related to sample size, feature stability, and liquidity of the market, which is more limited in emerging market settings.

Efficient Frontier Analysis

In the Efficient Frontier (EF) of finance theory, the portfolios with the greatest expected return are those that provide the greatest level of expected returns at each risk level. The efficient frontier sheds light on the BRICS countries in the structural risk-return characteristics of green and non-green asset universes.

Brazil

The non-green efficient frontier in Brazil portrays a high exposure to oil and gas companies (Petrobras, Vale) and Bitcoin. The Max Return portfolio has the highest potential for returns but the steepest risk gradient. The left extreme of the

frontier is anchored by the Min Variance portfolio, which has exposures to both agricultural and financial sectors. The green frontier led by Eletrobras and renewable energy equities shows a more moderate frontier slope with the Max Sharpe portfolio yielding good risk-adjusted returns and the Sortino portfolio reducing the exposure to downside risk.

India

Exposure to Reliance Industries, Indian Oil, and cryptocurrencies characterizes the non-green frontier of India. The Max Return portfolio has high returns with high risk. The Min Variance portfolio deals with technology and financial sector allocation risk management. The green frontier, powered by Adani Green Energy and renewable sector equities, has a smaller risk profile; the Max Sharpe portfolio enjoys the increasing green energy transition in India.

China

The non-green frontier of PetroChina and technology stocks in China adheres to the gradient and Sharpe-optimal positioning of the green frontier, which is in line with the parallel near-identical Maximum Sharpe Ratio results reported in Section 4.5. The green frontier, which is anchored by LONGi Green Energy and the green economy of solar and wind in China, is the way of policy-driven green economy development of the country, and the risk-return efficiency of both frontiers is similar. The Min Variance portfolio of

both universes illustrates a stable performance with lower returns.

Russia

The energy sector is a monopolist in the efficient frontier of Russia. The non-green frontier is the steep and risky one - the Max Return portfolio can generate spectacular returns with the increase of the energy prices, but the downside is increased by geopolitical risks and sanctions risk. The green frontier is not as steep, and the Max Sharpe portfolio has moderate returns and lower risk. There is a positive impact on the global renewable energy shift on the green portfolio of Russia, but there are significant obstacles to overcoming the policy stagnation and the lack of developed infrastructure for green elements.

South Africa

The efficient frontier of South Africa has different profiles for the two categories of portfolios. The non-green Max Sharpe portfolio with a standard deviation of 14.31 and a variance of 0.0205 attains a Sharpe ratio of 4.9400, representing the gains of efficiency that can be obtained through optimized exposure to mining and energy sectors in the country. The Sharpe ratio of the Naive Equal Weight portfolio is 1.2031 with a larger standard deviation of 67.69. The efficient frontier of the green portfolio is more flattened and at lower risk-adjusted returns, which is due to the high weight in the cryptocurrencies and their volatility.

Discussion

The results of this paper give valuable information on the relative performance of green and non-green portfolios in the BRICS economies, which form a complicated game between the creation of returns, the risks to which the portfolio is exposed, the optimisation policy, and the market structure. Through synthesising cross-country evidence, optimisation findings, and machine learning findings, several key themes can be identified that can be applied to academic literature and practical investment decision-making. The overall BRICS analysis indicates a definite trend; non-green portfolios are performing better than green portfolios in terms of absolute returns and overall

Sharpe ratios, especially in high-growth emerging economies like India and Brazil. This finding is consistent with the classical financial theory, according to which an increased payoff is frequently linked to increased exposure to risky industries like fossil fuel, commodities, and speculative assets like cryptocurrencies (Bhutto, Ahmed, Streimikiene, Shaikh, & Streimikis, 2020).

But this seeming superiority should be taken with a grain of salt. The increased returns that are seen in non-green portfolios are supported by heightened volatility, increased exposure to structural risk, particularly in countries where the economic performance is strongly associated with commodity cycles. Indicatively, Brazil and Russia can be seen to perform poorly on non-green performance because they are dependent on oil, gas, and mining industries. These industries are also cyclical in nature and prone to world market price changes, geopolitical crises, and regulatory changes. Green portfolios, on the other hand, have a more stable and consistent risk-adjusted performance in most BRICS countries, especially in China and India. This result is consistent with the emerging literature in the field of ESG that indicates that sustainability-based investing can contribute to increasing long-term stability by minimizing the exposure to regulatory, environmental, and reputational risks. The somewhat lower Sharpe ratios in other instances do not necessarily reflect inefficiency but are more indicative of a more conservative and resilient investment profile. (Amin et al., 2025) South Africa has a significant exception to this pattern, with non-green portfolios doing much better on a risk-adjusted performance of green portfolios. This can be credited to the economic makeup of this country, which is still highly reliant on mining and conventional energy sources, and comparatively underdeveloped in renewable energy infrastructure. This highlights the importance of country-specific factors in shaping portfolio outcomes. (Magazzino, Leong, & Faheem, 2026; Miranda, Moletta, Pedroso, Pilatti, & Picinin, 2021).

The Maximum Sharpe Ratio (MSR) strategy is always the most effective technique of

optimisation across all BRICS countries. This makes it more applicable as a standard of risk and return balancing, even in the turbulent emerging market set-ups. The preponderance of MSR indicates that mean-variance optimisation is resilient, notwithstanding the criticisms that it is sensitive to errors in estimation. Although the Minimum Variance strategy is effective in eliminating risk, it is always a poor strategy in terms of returns. This trade-off is likely because the strategy does not focus on growth, instead focusing on stability, and is therefore more appropriate for risk-averse investors than capital growth investors. Surprisingly, the Naive Equal Weight (1/N) strategy shows reasonable performance in absolute returns, but this is not able to compete with optimised strategies on a risk-adjusted basis. This substantiates already existing literature that argues that simple strategies can be robust, but they do not provide the efficiency benefits that are realised with optimisation. (Magazzino, Leong, & Faheem, 2026; Olanrewaju et al., 2025; Rezaei & Nezamabadi-Pour, 2025).

The Black-Litterman model does not perform well on most BRICS portfolios, and this could be indicative of the difficulty of using subjective investor opinions in highly volatile markets, lack of transparency, and structural heterogeneity. In the emerging markets where the forward-looking information is not that reliable, the assumptions behind Black-Litterman might not be quite as effective as in developed markets. The Sortino Ratio optimisation provides an interesting alternative, especially to investors who are worried about downside risk. Its high performance as compared with other strategies indicates that downside risk measures are especially pertinent in the emerging markets, where extreme negative returns are more prevalent. (Jayeola & Olatunji, 2025; Mikriukov, Sun, & Jiang, 2025).

The efficient frontier analysis gives a theoretical and graphical confirmation to the observed performance patterns. In BRICS countries, generally non-green portfolios have steeper efficient frontiers, which implies higher returns potential, but higher risk exposure. This particularly applies to those with resource dependence, like Russia and Brazil, where returns

are self-motivated by the movement of commodity prices. In contrast, green portfolios are more likely to exhibit smoother and more consistent efficient frontiers, which represent reduced volatility and slower movement of returns. The difference between green and non-green frontiers in China and India is comparatively low, which is why green energy and favorable governmental policies are making green investments competitive. The fact that the efficient frontiers in China are almost the same points to one especially useful fact, which is that in markets where green industries are highly developed and are a part of the overall economy, there is not such a strong distinction between a green and a non-green portfolio. This indicates that with the maturity of sustainability initiatives, green investments might be as efficient as traditional assets. (Bodnar & Schmid, 2009; Núñez-Mora & Sánchez-Ruenes, 2020).

The effective frontier in Russia highlights the vulnerability of excessive dependence on energy exports. Although non-green portfolios may yield high returns under favourable market conditions, they are also very susceptible to geopolitical shocks and sanctions that can strongly change the risk-return dynamics. The relatively flat green frontier of South Africa also depicts the difficulties of the country with an underdeveloped green sector. This is due to the fact that the few high-performing sustainable assets available limit the optimisation of the portfolio, leading to reduced risk-adjusted returns. (Syed, 2025).

Machine learning in portfolio analysis offers useful information to predict performance and model robustness. The findings suggest that machine learning models have the potential to identify meaningful patterns in financial data because there is moderate-to-good generalisation in most BRICS countries. Nonetheless, the existence of overfitting in some instances, especially within the non-green portfolio of Brazil and the green portfolio of South Africa, puts a serious constraint. These results align with the available literature, which highlights the fact that machine learning models are very sensitive to data quality, size, and stability of features. (Ślusarczyk & Ślepaczuk, 2025).

Conclusion

The study aimed to perform a cross-country comparison of green and non-green portfolio performance of the BRICS economies, including Brazil, Russia, India, China, and South Africa, by combining the conventional methods of portfolio optimisation, risk-adjusted performance, efficient frontier analysis, and machine learning-based forecasting. The research aimed to determine whether sustainable (green) investments can rival or even outshine conventional (non-green) portfolios in emerging market environments with greater volatility, structural inefficiencies, and non-homogeneous economic forces. The empirical evidence shows that there is a significant and steady deviation between the performance of green and non-green portfolios across BRICS countries. Non-green portfolios tend to have higher absolute returns and Sharpe ratios at the aggregate level, especially in India and Brazil, where commodities and energy markets and speculative assets exposure allow the portfolio to have higher returns. Nevertheless, this performance edge comes at a much greater volatility and greater exposure to downside, indicating the cyclical nature and macroeconomic exposure of traditional sectors.

Green portfolios, in contrast, although sometimes providing lower absolute returns, are more stable and provide more consistent risk-adjusted returns across most optimisation frameworks. They have a high level of performance, especially in China and India, where there is a good policy backing and structural investment in the renewable energy sector, which helps in enhanced efficiency and diminished portfolio risk. These results support the thesis that sustainable investments do not necessarily lead to maximization of returns but tend to increase portfolio resilience and downside protection, which is a crucial factor in an emerging market. Portfolio optimisation strategies analysis further validates the strength of the Maximum Sharpe Ratio (MSR) approach as the most effective approach consistently in both types of portfolios and in all BRICS countries. Minimum Variance is a good risk-reducing strategy with a restriction on the potential of returns, whereas the Naïve Equal Weight strategy is a good benchmark, but is always

less effective than optimisation-based strategies. The theoretically sophisticated Black-Litterman model has not been very effective in the BRICS context, probably because of challenges of effectively capturing the opinions of investors in turbulent and structurally heterogeneous markets. Meanwhile, the Sortino Ratio optimisation provides valuable improvements for downside-risk-sensitive investors, highlighting the importance of asymmetric risk measures in emerging economies.

These conclusions are also reinforced by the efficient frontier analysis, which compares the structure of green and non-green investment universes. The non-green portfolios can produce steeper frontiers, which signify greater return potential but expose them to higher risks, particularly in economies that are resource-dependent like Russia and Brazil. In comparison, green portfolios have smoother and less volatile frontiers, indicating reduced volatility and slower returns growth. Interestingly, convergence of the green and non-green efficient frontiers in China implies that the policy support and well-developed renewable infrastructure have the potential to close the performance gap between sustainable and conventional investments to a significant degree. There is an additional degree of predictability and insight into portfolio behaviour by the incorporation of machine learning models. Although models exhibit moderate forecasting accuracy and decent to good generalisation in most instances, overfitting, especially in Brazil and South Africa, underscores the difficulties in using data-based models in emerging markets. Problems like inadequate data, structural discontinuities, and market inefficiencies decrease predictive stability. Still, the findings yielded that machine learning can be a useful complementary tool to be used in combination with conventional financial optimisation methods. The study is, in general, an addition to the increasing literature on ESG investing, portfolio optimisation, and computational finance, as it offers a multi-dimensional comparative framework of BRICS economies. It indicates that the correlation between sustainability and financial performance is not universal but largely relies on country-

specific aspects, asset structure, and optimisation strategy. In summary, the results indicate that, although non-green portfolios are leading in terms of absolute returns, green portfolios provide an attractive substitute to the latter in terms of risk management, better stability, and rising competitiveness in risk-adjusted returns. With BRICS economies still building their renewable energy infrastructure and sustainability models, the performance disparity between green and non-green portfolios will close even more. Such a development represents a wider transformation of global financial markets towards a more balanced approach to profitability and environmental responsibility in their investment strategies, which underlines the sustainability of sustainable finance in the developing economies.

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APPENDIX A
All Figures and Tables

A.1 India — Green Portfolio

Table A.1: India Green Portfolio — Optimisation Strategy Performance Metrics

| Constraint | Portfolio Return | Portfolio Variance | Portfolio St. Dev | Portfolio Sharpe Ratio |
|-------------------------|------------------|--------------------|-------------------|------------------------|
| Naive Equal Weight | 1.0359 | 0.5087 | 0.7133 | 1.4523 |
| Maximum Return | 15.6769 | 272.0445 | 16.4938 | 0.9505 |
| Maximum Sharpe Ratio | 0.6819 | 0.0210 | 0.1450 | 4.7014 |
| Minimum Variance | 0.1905 | 0.0060 | 0.0772 | 2.4676 |
| Maximum Adjusted Sharpe | 0.6760 | 0.0207 | 0.1438 | 4.7012 |
| Maximum Skewness | 11.9299 | 156.5328 | 12.5113 | 0.9535 |
| Minimum Kurtosis | -0.5888 | 0.1182 | 0.3438 | -1.7123 |
| Short-Selling Portfolio | 0.6819 | 0.0210 | 0.1450 | 4.7014 |
| Sortino ratio | 43.53 | 75.8 | 80.48 | 0.5409 |
| Blacklittermen | 0.1131 | 0.0237 | 0.1539 | 0.7346 |

Figure A.2: India Green Portfolio — Machine Learning

Portfolio Metrics Comparison (Training Data vs Testing Data):

| Metric | Training Data | Testing Data |
|----------------------|---------------|--------------|
| 0 Return | 19.567954 | 0.254352 |
| 1 Variance | 340.655929 | 0.162364 |
| 2 Standard Deviation | 18.456867 | 0.402945 |
| 3 Sharpe Ratio | 1.059657 | 0.606416 |

Actual vs Predicted Portfolio Performance (Testing Period):

| Date | Actual Portfolio Performance |
|------------------------------|------------------------------|
| 0 2024-05-06 00:00:00+00:00 | 0.010089 |
| 1 2024-05-07 00:00:00+00:00 | -0.021783 |
| 2 2024-05-08 00:00:00+00:00 | -0.028184 |
| 3 2024-05-09 00:00:00+00:00 | -0.007890 |
| 4 2024-05-10 00:00:00+00:00 | -0.044145 |
| 5 2024-05-11 00:00:00+00:00 | -0.045501 |
| 6 2024-05-12 00:00:00+00:00 | -0.035395 |
| 7 2024-05-13 00:00:00+00:00 | -0.011611 |
| 8 2024-05-14 00:00:00+00:00 | -0.035710 |
| 9 2024-05-15 00:00:00+00:00 | 0.018326 |
| 10 2024-05-16 00:00:00+00:00 | 0.003093 |

Predicted Portfolio Performance

| | |
|----|-----------|
| 0 | 0.010089 |
| 1 | -0.021783 |
| 2 | -0.028184 |
| 3 | -0.007890 |
| 4 | -0.044145 |
| 5 | -0.045501 |
| 6 | -0.035395 |
| 7 | -0.011611 |
| 8 | -0.035710 |
| 9 | 0.018326 |
| 10 | 0.003093 |

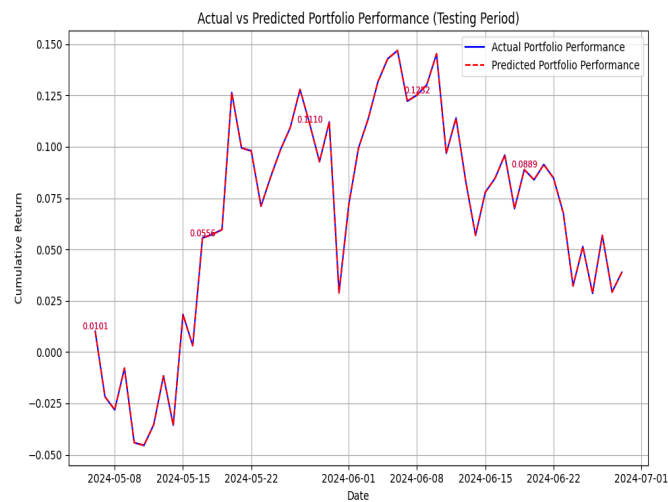


Figure A.3: India Green Portfolio — Machine Learning Training & Testing Performance

A.2 India — Non-Green Portfolio

Table A.2: India Non-Green Portfolio — Optimisation Strategy Performance Metrics

| Constraint | Portfolio Return | Portfolio Variance | Portfolio St. Dev. | Portfolio Sharpe Ratio |
|---------------------------|------------------|--------------------|--------------------|------------------------|
| Naive Equal Weight | 18069.3279 | 6794744.2814 | 2606.6730 | 6.9320 |
| Maximum Return | 144968.8989 | 444585982.7134 | 21085.2077 | 6.8754 |
| Maximum Sharpe Ratio | 62.6123 | 38.6271 | 6.2151 | 10.0743 |
| Minimum Variance | 18069.3279 | 6794744.2814 | 2606.6730 | 6.9320 |
| Maximum Adjusted Sharpe | 61.6331 | 36.7915 | 6.0656 | 10.1611 |
| Maximum Skewness | 2212.1273 | 34027190.0407 | 5833.2830 | 0.3792 |
| Minimum Kurtosis | 71.6656 | 57.3339 | 7.5719 | 9.4647 |
| Short-Selling Portfolio | 62.6123 | 38.6271 | 6.2151 | 10.0743 |
| Black-Litterman Portfolio | 0.1160 | 0.0244 | 0.1562 | 0.7430 |

Figure A.5: India Non-Green Portfolio — Machine Learning

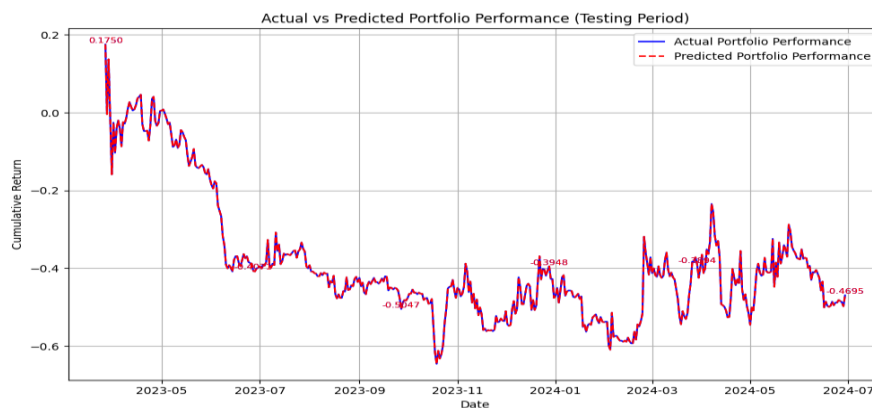
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Portfolio Metrics Comparison (Training Data vs Testing Data):
      Metric Training Data Testing Data
0      Return      0.939807      0.036112
1      Variance     3.912906      0.786992
2 Standard Deviation 1.978107      0.887126
3      Sharpe Ratio 0.470049      0.029434

Actual vs Predicted Portfolio Performance (Testing Period):
      Date Actual Portfolio Performance \
0 2023-03-27 00:00:00+00:00      0.175034
1 2023-03-28 00:00:00+00:00     -0.004071
2 2023-03-29 00:00:00+00:00      0.137042
3 2023-03-30 00:00:00+00:00     -0.008141
4 2023-03-31 00:00:00+00:00     -0.158752
.. ..
456 2024-06-25 00:00:00+00:00    -0.481683
457 2024-06-26 00:00:00+00:00    -0.484396
458 2024-06-27 00:00:00+00:00    -0.487110
459 2024-06-28 00:00:00+00:00    -0.497965
460 2024-06-29 00:00:00+00:00    -0.469471

Predicted Portfolio Performance
0      0.175034
1     -0.004071
2      0.137042
3     -0.008141
4     -0.158752
.. ..
456    -0.481683
457    -0.484396
458    -0.487110
459    -0.497965
460    -0.469471
    
```

Figure A.6: India Non-Green Portfolio — Machine Learning Training & Testing Performance



A.3 Russia — Green Portfolio

Table A.3: Russia Green Portfolio — Optimisation Strategy Performance Metrics

| Constraint | Portfolio Return | Portfolio Variance | Portfolio St. Dev. | Sharpe Ratio |
|-------------------------|------------------|--------------------|--------------------|--------------|
| Naive Equal Weight | 0.8027 | 0.5284 | 0.7269 | 1.1043 |
| Maximum Return | 15.6769 | 272.0445 | 16.4938 | 0.9505 |
| Maximum Sharpe Ratio | 0.5071 | 0.0229 | 0.1514 | 3.3494 |
| Minimum Variance | 0.0000 | 0.0000 | 0.0000 | 0.5280 |
| Maximum Adjusted Sharpe | 0.0492 | 0.0002 | 0.0147 | 3.3492 |
| Maximum Skewness | 2.0226 | 4.6352 | 2.1530 | 0.9395 |
| Minimum Kurtosis | 0.1301 | 0.0137 | 0.1172 | 1.1096 |
| Short-Selling Portfolio | 0.5071 | 0.0229 | 0.1514 | 3.3494 |
| Sortino ratio | 0.9198 | 0.4673 | 0.6821 | 2.4133 |
| Black littermen | 0.8027 | 0.5284 | 0.7269 | 1.1043 |

Figure A.8: Russia Green Portfolio — Machine Learning

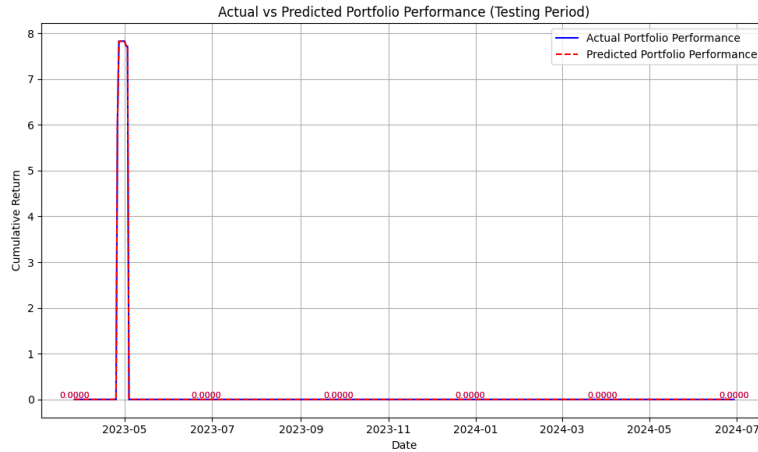
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Portfolio Metrics Comparison (Training Data vs Testing Data):
      Metric Training Data Testing Data
0      Return      19.567954      0.254352
1      Variance     340.655929      0.162364
2 Standard Deviation  18.456867      0.402945
3      Sharpe Ratio   1.059657      0.606416

Actual vs Predicted Portfolio Performance (Testing Period):
      Date Actual Portfolio Performance \
0 2024-05-06 00:00:00+00:00      0.010089
1 2024-05-07 00:00:00+00:00     -0.021783
2 2024-05-08 00:00:00+00:00     -0.028184
3 2024-05-09 00:00:00+00:00     -0.007890
4 2024-05-10 00:00:00+00:00     -0.044145
5 2024-05-11 00:00:00+00:00     -0.045501
6 2024-05-12 00:00:00+00:00     -0.035395
7 2024-05-13 00:00:00+00:00     -0.011611
8 2024-05-14 00:00:00+00:00     -0.035710
9 2024-05-15 00:00:00+00:00      0.018326
10 2024-05-16 00:00:00+00:00      0.003093

      Predicted Portfolio Performance
0      0.010089
1     -0.021783
2     -0.028184
3     -0.007890
4     -0.044145
5     -0.045501
6     -0.035395
7     -0.011611
8     -0.035710
9      0.018326
10     0.003093
    
```

Figure A.9: Russia Green Portfolio — Machine Learning Training & Testing Performance



A.4 Russia — Non-Green Portfolio

Table A.4: Russia Non-Green Portfolio — Optimisation Strategy Performance Metrics

| Constraint | Portfolio Return | Portfolio Variance | Portfolio St. Dev. | Sharpe Ratio |
|---------------------------|------------------|--------------------|--------------------|--------------|
| Naive Equal Weight | 0.3969 | 0.1954 | 0.4420 | 0.8979 |
| Maximum Return | 2.6380 | 37.5360 | 6.1267 | 0.4306 |
| Maximum Sharpe Ratio | 0.4413 | 0.0513 | 0.2265 | 1.9481 |
| Minimum Variance | 0.0801 | 0.0098 | 0.0992 | 0.8081 |
| Maximum Adjusted Sharpe | 0.4276 | 0.0482 | 0.2195 | 1.9478 |
| Maximum Skewness | 1.8070 | 33.0168 | 5.7460 | 0.3145 |
| Minimum Kurtosis | 0.1287 | 0.3306 | 0.5750 | 0.2239 |
| Short-Selling Portfolio | 0.4413 | 0.0513 | 0.2265 | 1.9481 |
| Sortino Ratio | 98.12 | 138.9 | 158.82 | 0.6178 |
| Black-Litterman Portfolio | 0.1044 | 0.1462 | 0.0214 | 0.7142 |

Figure A.11

Russia Non-Green Portfolio — Machine Learning

```

Portfolio Metrics Comparison (Training Data vs Testing Data):
Metric Training Data Testing Data
0 Return 2.558782 2.954829
1 Variance 41.813193 20.489759
2 Standard Deviation 6.466312 4.526562
3 Sharpe Ratio 0.394163 0.650566

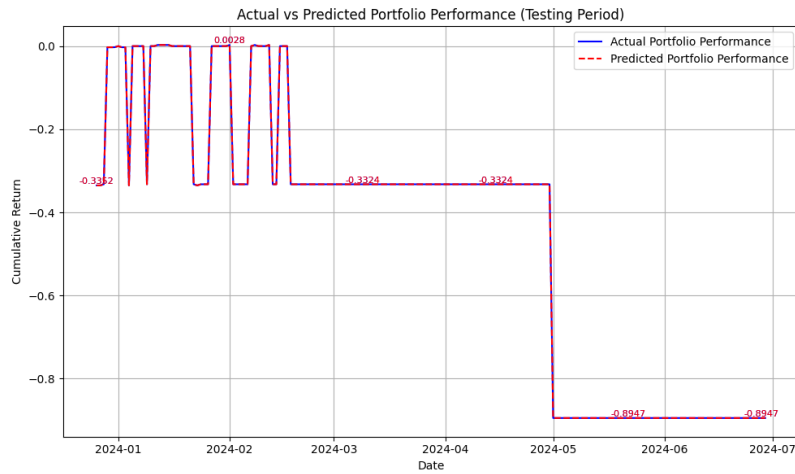
Actual vs Predicted Portfolio Performance (Testing Period):
Date Actual Portfolio Performance \
0 2023-03-27 00:00:00+00:00 0.000000e+00
1 2023-03-28 00:00:00+00:00 0.000000e+00
2 2023-03-29 00:00:00+00:00 0.000000e+00
3 2023-03-30 00:00:00+00:00 0.000000e+00
4 2023-03-31 00:00:00+00:00 0.000000e+00
...
456 2024-06-25 00:00:00+00:00 2.664535e-15
457 2024-06-26 00:00:00+00:00 2.664535e-15
458 2024-06-27 00:00:00+00:00 2.664535e-15
459 2024-06-28 00:00:00+00:00 2.664535e-15
460 2024-06-29 00:00:00+00:00 2.664535e-15

Predicted Portfolio Performance
0 0.000000e+00
1 0.000000e+00
2 0.000000e+00
3 0.000000e+00
4 0.000000e+00
...
456 2.664535e-15
457 2.664535e-15
458 2.664535e-15
459 2.664535e-15
460 2.664535e-15

[461 rows x 3 columns]
    
```

Figure A.12

Russia Non-Green Portfolio — Machine Learning Training & Testing Performance



A.5 Brazil — Green Portfolio

Table A.5

Brazil Green Portfolio — Optimisation Strategy Performance Metrics

| Constraint | Portfolio Return | Portfolio Variance | Portfolio St. Dev. | Portfolio Sharpe Ratio |
|-------------------------|------------------|--------------------|--------------------|------------------------|
| Naive Equal Weight | 0.8777 | 0.5061 | 0.7114 | 1.2337 |
| Maximum Return | 15.6769 | 272.0445 | 16.4938 | 0.9505 |
| Maximum Sharpe Ratio | 0.5047 | 0.0221 | 0.1485 | 3.3987 |
| Minimum Variance | 0.0000 | 0.0000 | 0.0000 | 0.4086 |
| Maximum Adjusted Sharpe | 0.0432 | 0.0002 | 0.0127 | 3.3986 |
| Maximum Skewness | 2.1015 | 4.9920 | 2.2343 | 0.9406 |
| Minimum Kurtosis | -0.2086 | 0.0383 | 0.1958 | -1.0658 |
| Short-Selling Portfolio | 0.5047 | 0.0221 | 0.1485 | 3.3987 |
| Sortino ratio | 69.14% | 103 | 145.13 | 0.4764 |
| Blacklitterman | 0.1100 | 0.0221 | 0.1487 | 0.7397 |

Figure A.14

Brazil Green Portfolio — Machine Learning

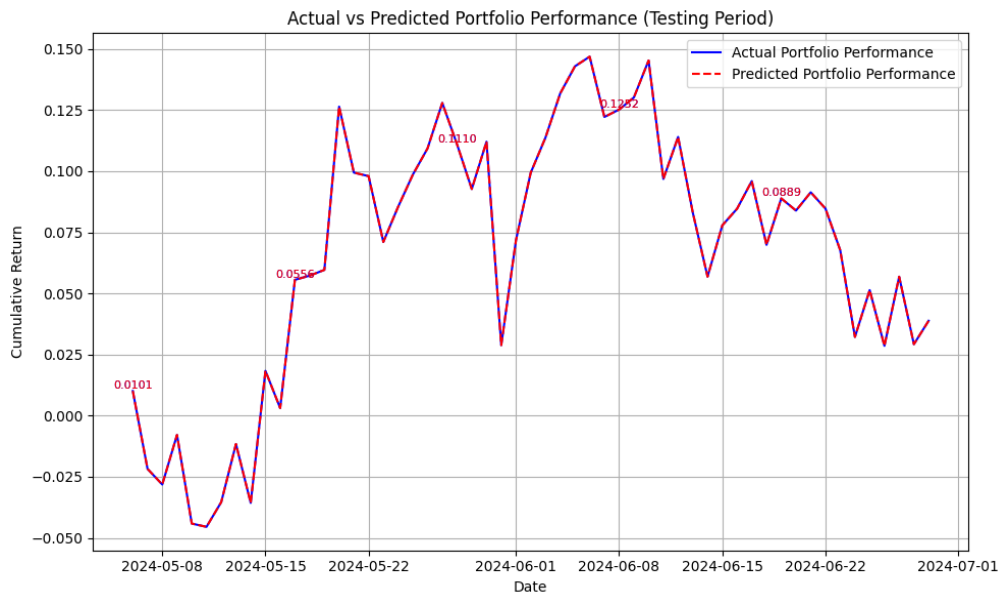
| Portfolio Metrics Comparison (Training Data vs Testing Data): | | | |
|---|--------------------|--------------|----------|
| Metric | Training Data | Testing Data | |
| 0 | Return | 19.567954 | 0.254352 |
| 1 | Variance | 340.655929 | 0.162364 |
| 2 | Standard Deviation | 18.456867 | 0.402945 |
| 3 | Sharpe Ratio | 1.059657 | 0.606416 |

| Actual vs Predicted Portfolio Performance (Testing Period): | | |
|---|------------------------------|-----------|
| Date | Actual Portfolio Performance | \ |
| 0 | 2024-05-06 00:00:00+00:00 | 0.010089 |
| 1 | 2024-05-07 00:00:00+00:00 | -0.021783 |
| 2 | 2024-05-08 00:00:00+00:00 | -0.028184 |
| 3 | 2024-05-09 00:00:00+00:00 | -0.007890 |
| 4 | 2024-05-10 00:00:00+00:00 | -0.044145 |
| 5 | 2024-05-11 00:00:00+00:00 | -0.045501 |
| 6 | 2024-05-12 00:00:00+00:00 | -0.035395 |
| 7 | 2024-05-13 00:00:00+00:00 | -0.011611 |
| 8 | 2024-05-14 00:00:00+00:00 | -0.035710 |
| 9 | 2024-05-15 00:00:00+00:00 | 0.018326 |
| 10 | 2024-05-16 00:00:00+00:00 | 0.003093 |

| Predicted Portfolio Performance | |
|---------------------------------|-----------|
| 0 | 0.010089 |
| 1 | -0.021783 |
| 2 | -0.028184 |
| 3 | -0.007890 |
| 4 | -0.044145 |
| 5 | -0.045501 |
| 6 | -0.035395 |
| 7 | -0.011611 |
| 8 | -0.035710 |
| 9 | 0.018326 |
| 10 | 0.003093 |

Figure A.15

Brazil Green Portfolio — Machine Learning Training & Testing Performance



A.6 Brazil — Non-Green Portfolio

Table A.6

Brazil Non-Green Portfolio — Optimisation Strategy Performance Metrics

| Constraint | Portfolio Return | Portfolio Variance | Portfolio St. Dev | Sharpe Ratio |
|-------------------------|------------------|--------------------|-------------------|--------------|
| Naive Equal Weight | 0.4205 | 0.1936 | 0.4400 | 0.9557 |
| Maximum Return | 4.8618 | 79.9462 | 8.9413 | 0.5437 |
| Maximum Sharpe Ratio | 0.4371 | 0.0365 | 0.1910 | 2.2883 |
| Minimum Variance | 0.0930 | 0.0089 | 0.0946 | 0.9833 |
| Maximum Adjusted Sharpe | 0.4263 | 0.0347 | 0.1863 | 2.2879 |
| Maximum Skewness | 4.7695 | 79.6985 | 8.9274 | 0.5343 |
| Minimum Kurtosis | -0.0033 | 0.0778 | 0.2789 | -0.0120 |
| Short-Selling Portfolio | 0.4371 | 0.0365 | 0.1910 | 2.2883 |
| Sortino ratio | 0.4237 | 0.0405 | 0.2012 | 2.1167 |
| Black littermen | 0.4205 | 0.1936 | 0.4400 | 0.9557 |

Figure A.17

Brazil Non-Green Portfolio — Machine Learning

Portfolio Metrics Comparison (Training Data vs Testing Data):

| | Metric | Training Data | Testing Data |
|---|--------------------|---------------|--------------|
| 0 | Return | 2.746592 | -0.238772 |
| 1 | Variance | 8.028001 | 4.034127 |
| 2 | Standard Deviation | 2.833373 | 2.008514 |
| 3 | Sharpe Ratio | 0.965843 | -0.123859 |

Actual vs Predicted Portfolio Performance (Testing Period):

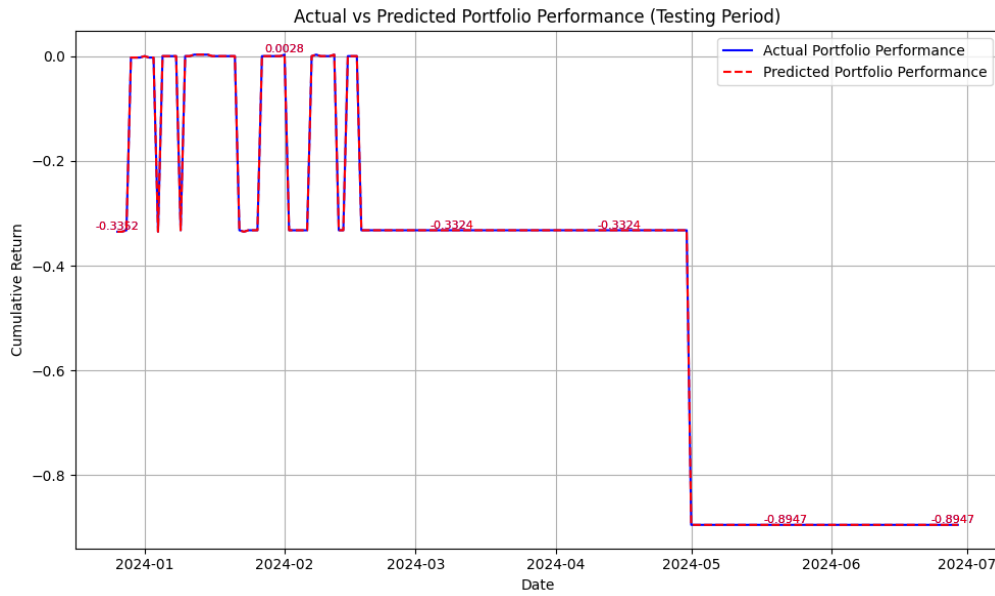
| | Date | Actual Portfolio Performance |
|-----|---------------------------|------------------------------|
| 0 | 2023-12-26 00:00:00+00:00 | -0.335180 |
| 1 | 2023-12-27 00:00:00+00:00 | -0.335180 |
| 2 | 2023-12-28 00:00:00+00:00 | -0.332410 |
| 3 | 2023-12-29 00:00:00+00:00 | -0.002770 |
| 4 | 2023-12-30 00:00:00+00:00 | -0.002770 |
| ... | ... | ... |
| 182 | 2024-06-25 00:00:00+00:00 | -0.894737 |
| 183 | 2024-06-26 00:00:00+00:00 | -0.894737 |
| 184 | 2024-06-27 00:00:00+00:00 | -0.894737 |
| 185 | 2024-06-28 00:00:00+00:00 | -0.894737 |
| 186 | 2024-06-29 00:00:00+00:00 | -0.894737 |

Predicted Portfolio Performance

| | |
|-----|-----------|
| 0 | -0.335180 |
| 1 | -0.335180 |
| 2 | -0.332410 |
| 3 | -0.002770 |
| 4 | -0.002770 |
| ... | ... |
| 182 | -0.894737 |
| 183 | -0.894737 |
| 184 | -0.894737 |
| 185 | -0.894737 |
| 186 | -0.894737 |

Figure A.18

Brazil Non-Green Portfolio — Machine Learning Training & Testing Performance



A.7 South Africa — Green Portfolio

Table A.7

South Africa Green Portfolio — Optimisation Strategy Performance Metrics

| Constraint | Portfolio Return | Portfolio Variance | Portfolio St. Dev. | Sharpe Ratio |
|-----------------------------|------------------|--------------------|--------------------|--------------|
| Black-Litterman | 0.1149 | 0.0245 | 0.1565 | 0.7346 |
| Optimized Sortino | 46.07% | 123 | 91.97 | 0.5009 |
| Best Portfolio (Max Sharpe) | 3.1363 | 0.2093 | 0.4575 | 6.8560 |
| Naive Equal Weight | -0.2207 | 0.0371 | 0.1927 | -1.1454 |
| Maximum Return | 0.6767 | 0.0865 | 0.2940 | 2.3012 |
| Maximum Sharpe Ratio | 3.1363 | 0.2093 | 0.4575 | 6.8560 |
| Minimum Variance | 0.1138 | 0.0078 | 0.0884 | 1.2870 |
| Maximum Adjusted Sharpe | 3.0245 | 0.1947 | 0.4413 | 6.8541 |
| Maximum Skewness | 2.3656 | 1.9022 | 1.3792 | 1.7152 |
| Minimum Kurtosis | 0.1498 | 0.3019 | 0.5495 | 0.2727 |

Figure A.20

South Africa Green Portfolio — Machine Learning

Portfolio Metrics Comparison (Training Data vs Testing Data):

| Metric | Training Data | Testing Data |
|----------------------|---------------|--------------|
| 0 Return | 0.687209 | -0.189098 |
| 1 Variance | 0.099068 | 0.105381 |
| 2 Standard Deviation | 0.314750 | 0.324625 |
| 3 Sharpe Ratio | 2.151575 | -0.613318 |

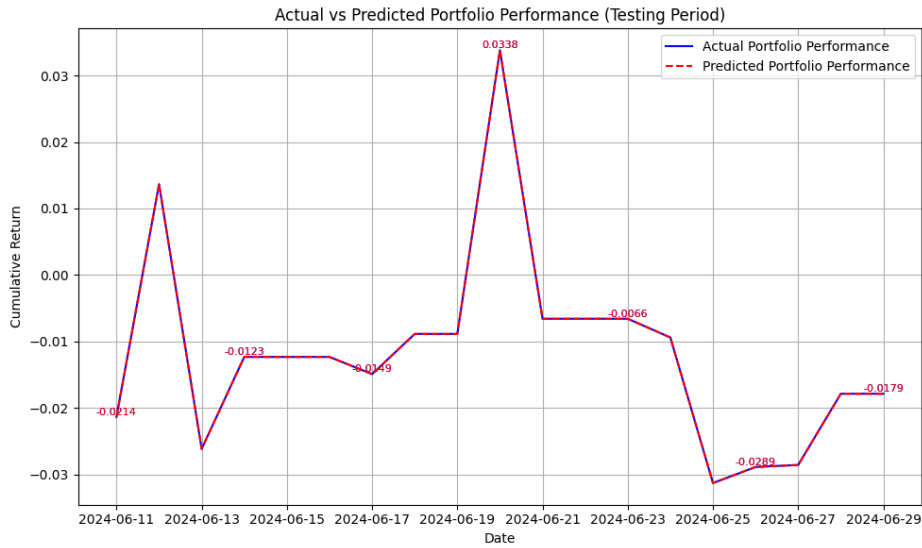
Actual vs Predicted Portfolio Performance (Testing Period):

| Date | Actual Portfolio Performance \ |
|------------------------------|--------------------------------|
| 0 2024-06-11 00:00:00+00:00 | -0.021364 |
| 1 2024-06-12 00:00:00+00:00 | 0.013672 |
| 2 2024-06-13 00:00:00+00:00 | -0.026168 |
| 3 2024-06-14 00:00:00+00:00 | -0.012328 |
| 4 2024-06-15 00:00:00+00:00 | -0.012328 |
| 5 2024-06-16 00:00:00+00:00 | -0.012328 |
| 6 2024-06-17 00:00:00+00:00 | -0.014915 |
| 7 2024-06-18 00:00:00+00:00 | -0.008868 |
| 8 2024-06-19 00:00:00+00:00 | -0.008868 |
| 9 2024-06-20 00:00:00+00:00 | 0.033827 |
| 10 2024-06-21 00:00:00+00:00 | -0.006584 |

| Date | Predicted Portfolio Performance |
|------|---------------------------------|
| 0 | -0.021364 |
| 1 | 0.013672 |
| 2 | -0.026168 |
| 3 | -0.012328 |
| 4 | -0.012328 |
| 5 | -0.012328 |
| 6 | -0.014915 |
| 7 | -0.008868 |
| 8 | -0.008868 |
| 9 | 0.033827 |
| 10 | -0.006584 |

Figure A.21

South Africa Green Portfolio — Machine Learning Training & Testing Performance



A.8 South Africa — Non-Green Portfolio

Table A.8

South Africa Non-Green Portfolio — Optimisation Strategy Performance Metrics

| Constraint | Portfolio Return | Portfolio Variance | Portfolio St. Dev | Portfolio Sharpe Ratio |
|-------------------------|------------------|--------------------|-------------------|------------------------|
| Max Sharpe | 0.7071 | 0.0205 | 0.1431 | 4.9400 |
| Naive Equal Weight | 0.8144 | 0.4583 | 0.6769 | 1.2031 |
| Max Return | 0.8502 | 0.3496 | 0.5913 | 1.4367 |
| Max Sharpe Ratio | 0.8990 | 0.4328 | 0.6576 | 2.4700 |
| Min Variance | 0.5333 | 0.1377 | 0.3712 | 1.5678 |
| Max Adjusted Sharpe | 0.6063 | 0.2287 | 0.4783 | 1.8260 |
| Max Skewness | 0.5518 | 0.2490 | 0.4990 | 1.8580 |
| Min Kurtosis | 0.4861 | 0.1673 | 0.4090 | 1.1990 |
| Short-Selling Portfolio | 0.7419 | 0.3896 | 0.6240 | 1.2811 |
| Optimized Sortino | 0.9198 | 0.4673 | 0.6821 | 2.4133 |
| Black Litterman | 0.1200 | 0.0261 | 0.1615 | 0.7433 |

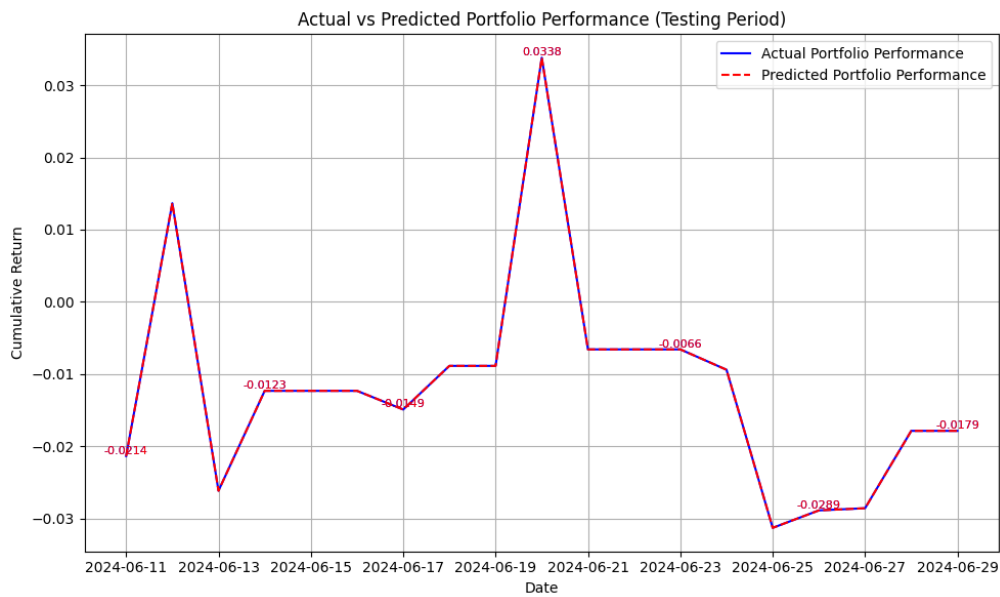
Figure A.23

South Africa Non-Green Portfolio — Machine Learning

| Portfolio Metrics Comparison (Training Data vs Testing Data): | | | |
|---|--------------------|--------------|-----------|
| Metric | Training Data | Testing Data | |
| 0 | Return | 0.687209 | -0.189098 |
| 1 | Variance | 0.099068 | 0.105381 |
| 2 | Standard Deviation | 0.314750 | 0.324625 |
| 3 | Sharpe Ratio | 2.151575 | -0.613318 |

| Actual vs Predicted Portfolio Performance (Testing Period): | | |
|---|------------------------------|---------------------------------|
| Date | Actual Portfolio Performance | Predicted Portfolio Performance |
| 0 2024-06-11 00:00:00+00:00 | -0.021364 | -0.021364 |
| 1 2024-06-12 00:00:00+00:00 | 0.013672 | 0.013672 |
| 2 2024-06-13 00:00:00+00:00 | -0.026168 | -0.026168 |
| 3 2024-06-14 00:00:00+00:00 | -0.012328 | -0.012328 |
| 4 2024-06-15 00:00:00+00:00 | -0.012328 | -0.012328 |
| 5 2024-06-16 00:00:00+00:00 | -0.012328 | -0.012328 |
| 6 2024-06-17 00:00:00+00:00 | -0.014915 | -0.014915 |
| 7 2024-06-18 00:00:00+00:00 | -0.008868 | -0.008868 |
| 8 2024-06-19 00:00:00+00:00 | -0.008868 | -0.008868 |
| 9 2024-06-20 00:00:00+00:00 | 0.033827 | 0.033827 |
| 10 2024-06-21 00:00:00+00:00 | -0.006584 | -0.006584 |

Figure A.24: South Africa Non-Green Portfolio — Machine Learning Training & Testing Performance



A.9 China — Green Portfolio

Table A.9: China Green Portfolio — Optimisation Strategy Performance Metrics

| Constraint | Portfolio Return | Portfolio Variance | Portfolio St. Dev | Portfolio Sharpe Ratio |
|-------------------------|------------------|--------------------|-------------------|------------------------|
| Naive Equal Weight | 1.0093 | 0.6090 | 0.7804 | 1.2934 |
| Maximum Return | 15.6769 | 272.0445 | 16.4938 | 0.9505 |
| Maximum Sharpe Ratio | 1.0778 | 0.0520 | 0.2281 | 4.7261 |
| Minimum Variance | 0.1010 | 0.0052 | 0.0723 | 1.3964 |
| Maximum Adjusted Sharpe | 1.0086 | 0.0456 | 0.2135 | 4.7248 |
| Maximum Skewness | 8.4490 | 79.2399 | 8.9017 | 0.9491 |
| Minimum Kurtosis | 1.0654 | 0.2109 | 0.4592 | 2.3200 |
| Short-Selling Portfolio | 1.0778 | 0.0520 | 0.2281 | 4.7261 |
| Sortino Ratio | 1.0093 | 0.6090 | 0.7804 | 1.2934 |
| Black-Litterman | 1.0093 | 0.6090 | 0.7804 | 1.2934 |

Figure A.26: China Green Portfolio — Machine Learning

Portfolio Metrics Comparison (Training Data vs Testing Data):

| Metric | Training Data | Testing Data |
|----------------------|---------------|--------------|
| 0 Return | 19.567954 | 0.254352 |
| 1 Variance | 340.655929 | 0.162364 |
| 2 Standard Deviation | 18.456867 | 0.402945 |
| 3 Sharpe Ratio | 1.059657 | 0.606416 |

Actual vs Predicted Portfolio Performance (Testing Period):

| Date | Actual Portfolio Performance \ | Predicted Portfolio Performance |
|------------------------------|--------------------------------|---------------------------------|
| 0 2024-05-06 00:00:00+00:00 | 0.010089 | 0.010089 |
| 1 2024-05-07 00:00:00+00:00 | -0.021783 | -0.021783 |
| 2 2024-05-08 00:00:00+00:00 | -0.028184 | -0.028184 |
| 3 2024-05-09 00:00:00+00:00 | -0.007890 | -0.007890 |
| 4 2024-05-10 00:00:00+00:00 | -0.044145 | -0.044145 |
| 5 2024-05-11 00:00:00+00:00 | -0.045501 | -0.045501 |
| 6 2024-05-12 00:00:00+00:00 | -0.035395 | -0.035395 |
| 7 2024-05-13 00:00:00+00:00 | -0.011611 | -0.011611 |
| 8 2024-05-14 00:00:00+00:00 | -0.035710 | -0.035710 |
| 9 2024-05-15 00:00:00+00:00 | 0.018326 | 0.018326 |
| 10 2024-05-16 00:00:00+00:00 | 0.003093 | 0.003093 |

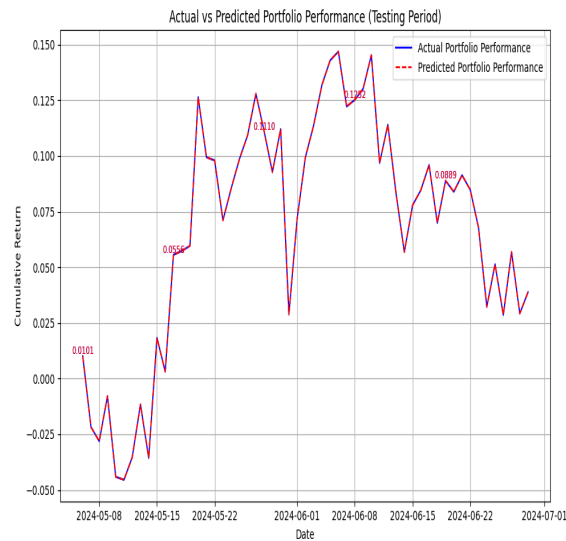


Figure A.27: China Green Portfolio — Machine Learning Training & Testing Performance

A.10 China — Non-Green Portfolio

Table A.10: China Non-Green Portfolio — Optimisation Strategy Performance Metrics

| Constraint | Portfolio Return | Variance | Standard Deviation | Sharpe Ratio |
|-------------------------|------------------|----------|--------------------|--------------|
| Naive Equal Weight | 0.3244 | 0.1436 | 0.3789 | 0.8561 |
| Maximum Return | 2.1565 | 33.3652 | 5.7763 | 0.3733 |
| Maximum Sharpe Ratio | 0.2605 | 0.0256 | 0.1599 | 1.6294 |
| Minimum Variance | 0.0656 | 0.0072 | 0.0851 | 0.7709 |
| Maximum Adjusted Sharpe | 0.2590 | 0.0253 | 0.1590 | 1.6293 |
| Maximum Skewness | 1.8064 | 33.0054 | 5.7450 | 0.3144 |
| Minimum Kurtosis | 0.0939 | 0.9382 | 0.9686 | 0.0969 |
| Short-Selling Portfolio | 0.2605 | 0.0256 | 0.1599 | 1.6294 |
| Black-Litterman | -82833 | 0.0527 | 0.2296 | -36072 |

Figure A.29: China Non-Green Portfolio — Machine Learning

Portfolio Metrics Comparison (Training Data vs Testing Data):

| Metric | Training Data | Testing Data |
|----------------------|---------------|--------------|
| 0 Return | 0.939807 | 0.036112 |
| 1 Variance | 3.912906 | 0.786992 |
| 2 Standard Deviation | 1.978107 | 0.887126 |
| 3 Sharpe Ratio | 0.470049 | 0.029434 |

Actual vs Predicted Portfolio Performance (Testing Period):

| Date | Actual Portfolio Performance |
|-------------------------------|------------------------------|
| 0 2023-03-27 00:00:00+00:00 | 0.175034 |
| 1 2023-03-28 00:00:00+00:00 | -0.004071 |
| 2 2023-03-29 00:00:00+00:00 | 0.137042 |
| 3 2023-03-30 00:00:00+00:00 | -0.008141 |
| 4 2023-03-31 00:00:00+00:00 | -0.158752 |
| ... | ... |
| 456 2024-06-25 00:00:00+00:00 | -0.481683 |
| 457 2024-06-26 00:00:00+00:00 | -0.484396 |
| 458 2024-06-27 00:00:00+00:00 | -0.487110 |
| 459 2024-06-28 00:00:00+00:00 | -0.497965 |
| 460 2024-06-29 00:00:00+00:00 | -0.469471 |

| Date | Predicted Portfolio Performance |
|------|---------------------------------|
| 0 | 0.175034 |
| 1 | -0.004071 |
| 2 | 0.137042 |
| 3 | -0.008141 |
| 4 | -0.158752 |
| ... | ... |
| 456 | -0.481683 |
| 457 | -0.484396 |
| 458 | -0.487110 |
| 459 | -0.497965 |
| 460 | -0.469471 |

[461 rows x 3 columns]

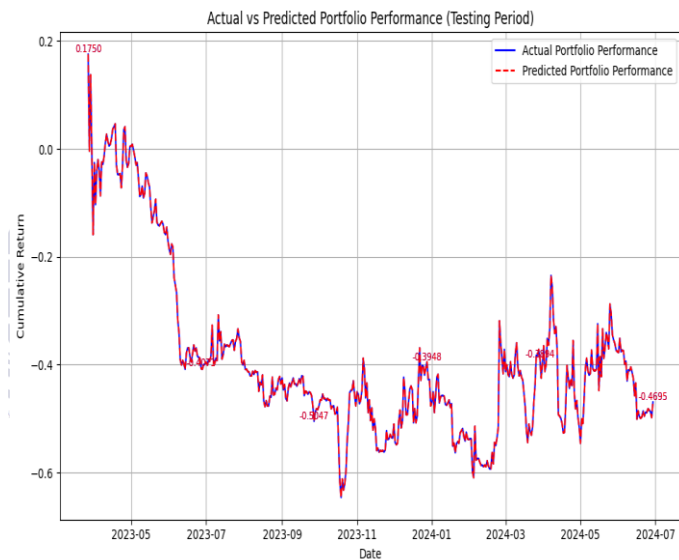


Figure A.30: China Non-Green Portfolio — Machine Learning Training & Testing Performance

A.11 Efficient Frontier Charts — All Countries

Figure A.31: Brazil — Green Portfolio Efficient Frontier

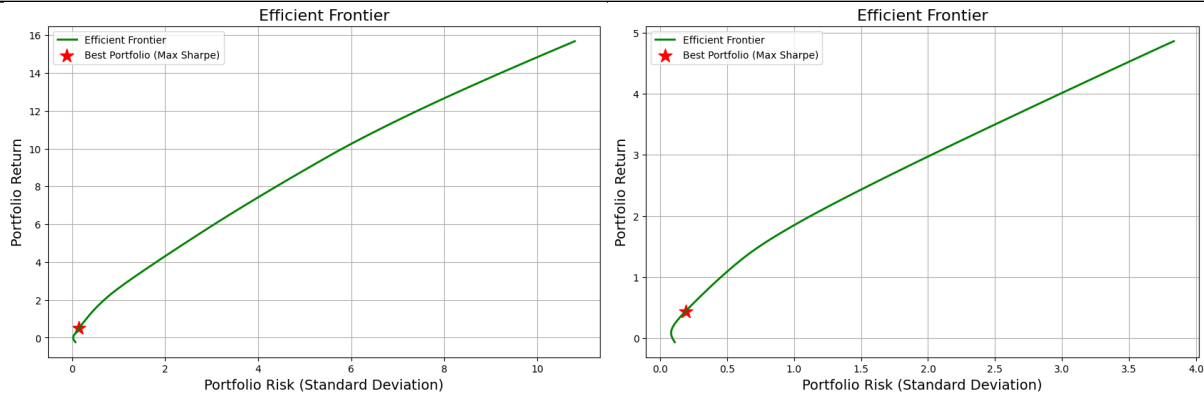


Figure A.32: Brazil — Non-Green Portfolio Efficient Frontier



Figure A.33: India — Green Portfolio Efficient Frontier

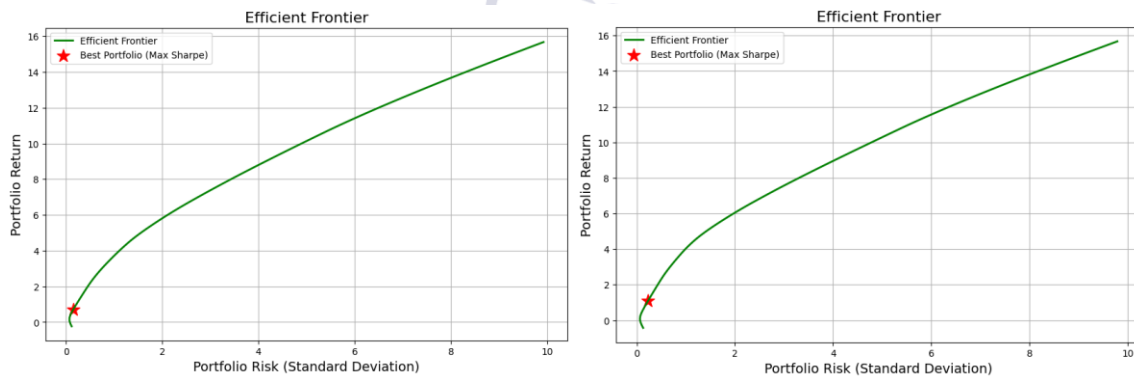


Figure A.34: India — Non-Green Portfolio Efficient Frontier

Figure A.35: China — Green Portfolio Efficient Frontier

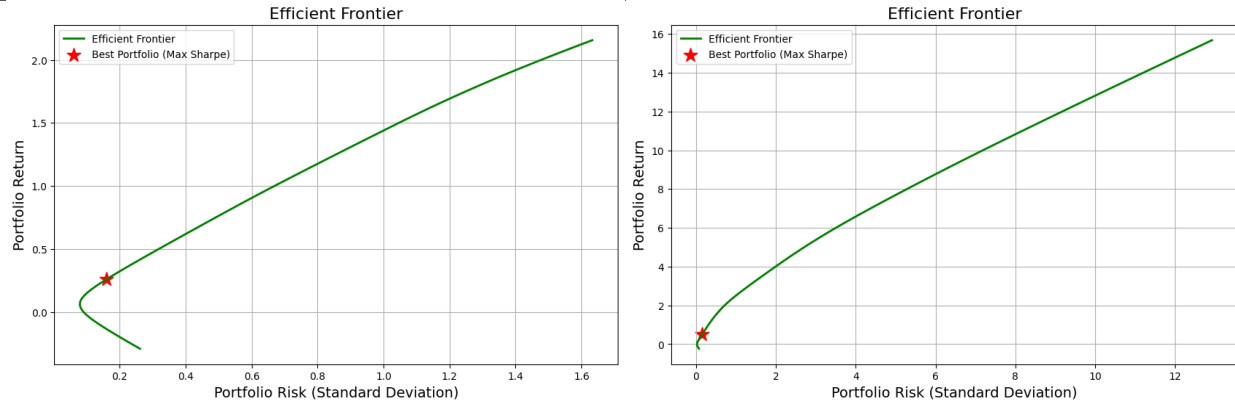


Figure A.36: China — Non-Green Portfolio Efficient Frontier

Figure A.37: Russia — Green Portfolio Efficient Frontier

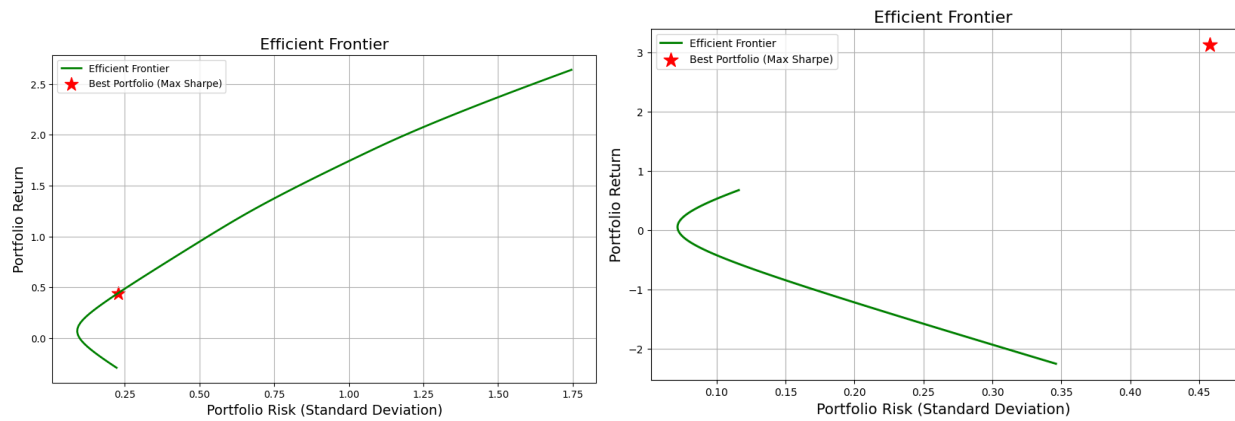


Figure A.38: South Africa — Green/Non-Green Portfolio Efficient Frontier