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Multi-Asset Portfolio Optimization for Green and Non-Green Cryptocurrencies in G7 Using Machine Learning

Syeda Fizza Abbas[1], Sumiya Tahir[2] & Sayyid Haider Mustafa Rizavi[3]

[1] *Assistant Professor, Kinnaird College for Women Lahore, Pakistan, Email: fizza.abbas@kinnaird.edu.pk*
[2] *Research Scholar, Kinnaird College for Women Lahore, Pakistan, Email: Sumiya.tahir1996@gmail.com*
[3] *Faculty at UCP Business School, University of Central Punjab, Email: sayyidhaider.rizvi@ucp.edu.pk*

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Corresponding Author:
Syeda Fizza Abbas
Email:
fizza.abbas@kinnaird.edu.pk

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ABSTRACT

This study examines the financial performance of diversified portfolios composed of various asset categories, including green cryptocurrencies, non-green cryptocurrencies, energy cryptocurrencies, stocks of leading companies, stocks of top energy companies, and stocks of prominent sustainable companies within the context of G7 nations. Additionally, it investigates the financial performance of green and non-green cryptocurrency portfolios across these regions. It aims to compare returns while examining the initiatives undertaken by these countries to foster sustainable financial systems. The research also explores how investors can leverage portfolio optimization to enhance returns in the rapidly evolving digital currency market. The study employs two machine learning techniques. First, six constraints, including maximum Sharpe ratio, minimum variance, maximum return, Sortino ratio, and Black-Litterman model, were applied to build portfolios for green and non-green cryptocurrencies. The model started with an 80%-20% train-test separation to find suitable allocations that it improved using full dataset retraining. The results explained that the highest Sharpe ratio portfolio generated the finest performance in the U.S. and Japan because of their strong financial market institutions and active participation from institutions. The investment cultures of Canada and Italy led to their selection of minimum variance portfolios. The Black-Litterman model worked well in the UK to produce equilibrium between market expectations and real risk-returns while German investors chose maximum return portfolios due to their risk tolerance. The French financial industry put risk-adjusted returns at the forefront thus the optimized Sortino ratio strategy proved most appropriate. A comparison between green and non-green portfolios shows that green portfolios regularly exhibited lower volatility together with superior risk-adjusted returns especially when sustainability policies were clearly defined in the nation. The higher returns from non-green portfolios came alongside higher speculative risk which made them susceptible to market volatility. This study demonstrated that selecting portfolios should be done based on specific market features that vary from country to country. Those who need stable long-term returns can achieve it through green investing while investors with high tolerance for risks can spend in non-green investments. Future studies should concentrate on developing dynamic rebalancing methods for portfolios while integrating decentralized finance (DeFi) technology to optimize portfolio management systems.

Introduction

People working in today's finance industry use portfolio management techniques because they wish to manage multiple asset types for optimal risk and return balance. Investors need to develop ideal portfolios since they offer structured methods to manage financial risks and boost market profits. Organizations that manage sensitive financial data must utilize cryptocurrencies because they provide improved security capabilities. On blockchain transaction systems maintain an unalterable state because they use cryptographic methods that protect against both dishonest tampering and fraud attempts. Every transaction exists on a public ledger which enables trust between customers and partners because all records are transparent for verification purposes (Petrova, Nikiforov, Klochko, Litti, Stepanova, & Protasov, 2020). Through self-executing contracts users achieve streamlined execution of operations while increasing trust and preventing disputes due to their embedded terms which guarantee satisfactory business agreement compliance (M. Luo & Yu, 2022).

Using principles from Markowitz's portfolio theory investors achieve optimal risk reduction while striving for desirable returns by making strategic asset comparisons to find the most appropriate risk profile (Ding, 2024). Historical performance data provides the expected return as the main metric while portfolio variability or return standard deviation serves as the risk measurement method (Baydalin, 2024). Optimal portfolio construction requires constraints to enable investors in designing investment plans based on their specific risk management preferences along with their financial targets and regulatory boundaries (Ricca & Scozzari, 2024). Portfolio constraints help managers achieve efficient risk-return allocation through specific boundaries that regulate the portfolio elements and attributes. A risk-averse investor goes for minimum variance portfolios mainly to decrease potential losses rather than pursuing aggressive investors who prioritize higher returns no matter the increased risk. Moral and legal requirements can be upheld through constraints that prevent short selling and bar investments in specific sectors. Through constraints the investor obtains protection from unnecessary risks while keeping their portfolio aligned with their personal beliefs and mandates (Mi & Xu, 2023).

Portfolio optimization achieves stronger accuracy and resilience when the procedure incorporates specific restrictions. Investors can shape return distribution when they add skewness and kurtosis constraints to their portfolios so they get more routine small wins with less significant losses. The control of extreme risks and the delivery of steady performance becomes particularly vital(Meng & Ma, 2023). However, these customized restrictions allow for the construction of a portfolio that is more appropriate for fulfilling the various and unique demands of individual investors in addition to being optimized for predicted performance resulting in more satisfying and long-lasting investment outcomes(Irhamni, 2024).

The cryptocurrency market develops toward sustainable digital currencies which work toward reducing environmental effects of cryptocurrency mining operations and financial transactions. Green cryptocurrencies provide substantial value to different investor groups because they connect monetary success to environmental conservation while following emerging rule systems. Retail investors and institutional investors alongside portfolio managers deal with separate challenges because they need to navigate the unpredictable cryptocurrency market. Through behavioral finance knowledge and portfolio management awareness these investors can build investment plans which reduce risks and generate lasting profits and contribute to environmental initiatives (Castellanos, Coll-Mayor, & Notholt, 2017). Such value-driven strategies both fulfill ethical standards and lead to better investment participation. The combination of overconfidence and herding behavior among retail investors leads them to make hasty investment choices in traditional cryptocurrencies.

The growing interest in green cryptocurrency indicates the G7 nations strongly support sustainability initiatives. Green cryptocurrencies experience increasing popularity because the G7 governments focus their efforts to fight global warming and implement sustainable energy technicalities. The study details how investors can integrate these cryptocurrencies into their portfolios to illustrate practical methods for improving sustainability of standard investment assets including stocks and bonds. The designed energy cryptocurrencies work in line with G7 long-term energy policy goals for cleaner energy by enhancing market efficiency. The research findings hold significant value for investors who wish to diversify their portfolios across multiple global markets along with those in charge of financial market directions who want to shape sustainable investments and technological advancements (Khalfaoui, Hammoudeh, & Rehman, 2023).

A complete research method supports this study to analyze portfolio optimization within digital financial systems. Daily return data was collected from asset classes including stocks and commodities together with non-green, green and renewable energy cryptocurrencies. Portfolio development depends on an asset risk analysis of historical returns combined with machine learning methods that utilize neural networks together with ensemble methods (Ramkumar, 2021). The purpose of this study involves obtaining precise forecasting results together with understanding asset class behavior by implementing machine learning within optimization systems. By using this multidisciplinary approach researchers explain how modern portfolio management practices benefit from innovative technology (Akyildirim, Goncu, & Sensoy, 2021).

The research gives vital information to policymakers and investors and asset managers about portfolio sustainability within a transforming digital finance framework (Ali, Khurram, Sensoy, & Vo, 2024). This research will add to the body of knowledge by bridging the gap between conventional finance theories and the newly developing field of digital finance. It will also provide insight into how green cryptocurrencies might influence sustainable investing methods in the future The study adapts to this changing landscape by including green and energy cryptocurrencies in the analysis, offering insightful information on the best ways to design portfolios that strike a balance between financial returns and environmental concerns. This all-encompassing strategy highlights the study's applicability in addressing new developments in the digital asset market and investors' changing needs(Huang, Han, Newton, Platanakis, Stafylas, & Sutcliffe, 2023).

Research Hypothesis

H_1: Machine learning-driven portfolio optimization improves risk-adjusted returns compared to conventional financial models by dynamically adapting to market conditions.

H_2: Green cryptocurrency portfolios demonstrate lower volatility and superior risk-adjusted performance relative to non-green portfolios, particularly in countries with strong sustainability regulations.

H_3: Portfolio optimization strategies, including maximum Sharpe ratio, maximum return, minimum variance, and Sortino ratio alongside the Black-Litterman model present different levels of effectiveness between G7 nations based on their unique financial steadiness patterns and authorities' frameworks together with investor attitude toward risk.

H_4: The stability and reliability of machine learning-optimized cryptocurrency portfolios is validated by robust testing, ensuring consistent performance in volatile market environments.

Research Objectives

1. Evaluation of portfolio optimization through machine learning algorithms, to determine if it produces superior risk-adjusted returns than traditional financial models.
2. To examine volatility assessment accompanied by risk-adjusted evaluation of green cryptocurrency portfolios including non-green portfolios in countries implementing strict sustainability regulations.
3. To investigate how financial stability policies together with regulatory frameworks and risk tolerance choices of investors affect the optimization strategies for the maximum Sharpe ratio, minimum variance and Black-Litterman model across different G7 nations.
4. To validate the stability and reliability after conducting robustness testing on machine learning-based cryptocurrency portfolios for volatile market environments.

Literature Review

The financial industry has experienced radical changes thanks to machine learning adoption for investment analysis because data-based decisions now extend past normal statistical methods. Active investment and passive index represent two fundamental investment strategies among many others which have distinct aims and objectives. The methods described by Koesoemasari, Haryono, Trinugroho, and Setiawan (2022) guide investors to optimize capital distribution to meet financial targets alongside risk management effectiveness. The study summarizes the most important research results in the area highlighting the revolutionary effect of machine learning on improving investment strategies and offering a prediction course on this multidisciplinary topic.

According to (Chen, Zhang, & Jia, 2022; Han, Kim, & Enke, 2023; Wen-Chen & Ku-Jun, 2005) an investment strategy is a collection of guiding principles for making assets. Diversification and asset allocation are the investment techniques used to build optimal portfolios. This study examines the connections between different cryptocurrencies and the other traditional assets that support them to build and model superior portfolios that outperform the market. The market for cryptocurrencies and all of its supporting infrastructure are expanding yearly(Almeida & Gonçalves, 2024). A growing number of institutional and individual investors of all backgrounds are investing in and trading cryptocurrencies as a result of its accessibility. The market capitalization of Ethereum and Bitcoin as well as the cryptocurrency market overall has increased significantly in recent years. Additionally, a growing number of investors are gaining interest in the cryptocurrency market and the profits that may be made there(Cai, Xue, & Zhou, 2024). Certain theories may continue to be applied in the cryptocurrency market even though their bodies were developed for a different market before the development of cryptocurrencies.

To optimise the risk and return profile, most research uses optimisation techniques (Markowitz, 1952). Markowitz's portfolio theory revolves around the risk-return characteristics of portfolios, which are designed to maximize yields for an identified degree of volatility while minimizing variability for a certain threshold of return. It is possible to compute the risk-return profile using Sharpe (1977). Researchers are typically drawn to the investment qualities of cryptocurrencies for two reasons. Nonetheless, cryptocurrencies are typically not linked to any monetary policy or authority, and this is especially true when it comes to portfolio development. Since their debut, cryptocurrencies have demonstrated both incredible profits and very high volatility. Because of these features, researchers have started looking into the impact of include cryptocurrencies in optimised portfolios; most of these studies concentrate on Bitcoin. (Aggarwal, Batra, Sharma, Dhingra, Yadav, & Kumar, 2024; Akhtaruzzaman, Sensoy, & Corbet, 2020; Andrianto & Diputra, 2017; Eisl, Gasser, & Weinmayer, 2015; Guesmi, Saadi, Abid, & Ftiti, 2019; Henriques &

Sadorsky, 2018; Klein, Thu, & Walther, 2018; Mensi, Gubareva, Al-Yahyaee, Teplova, & Kang, 2024; Platanakis & Urquhart, 2020; Sahu, Ochoa Vázquez, Ramírez, & Kim, 2024; Symitsi & Chalvatzis, 2019; Ustaoglu, 2023). According to Briere, Oosterlinck, and Szafarz (2015), their study was the first to look at Bitcoin's investment potential in a portfolio context. Using Bitcoin and these assets' weekly returns from 2010 to 2013. This study employed a viewpoint of a US investor with a diverse portfolio that includes overseas bonds, currencies, stocks, unconventional real estate, and commodities assets. This data shows that over the study period, Bitcoin had a high monthly volatility of 23.43 percent and a strong average monthly return of 7.8%. It also demonstrated how little Bitcoin at the time correlated with other asset types.

Green cryptocurrencies versus non-green cryptocurrencies are brought into play which adds a new dimension to asset allocation strategies in place such that investors have to consider the environmental impact apart from those regular risk-return issues (Ejaz, Ashraf, Hassan, & Gupta, 2022). Including the green cryptocurrencies in portfolio allocation can grant investors exposure to environmentally friendly technologies and mechanisms while they may be cutting away from the bonds with the projects associated with carbon-laden promises (Ali et al., 2024). The findings demonstrated that the benefits of diversity offered by green cryptocurrencies outweigh those of non-green (energy-intensive) cryptocurrencies, at least when it comes to comparison. The green cryptocurrencies that provide investors the greatest benefits of diversity are Cardano and Teos, followed by EOS, Steller, and IOTA(Ali et al., 2024).

Conceptual Framework

Green Cryptocurrency Portfolio (Model 01)

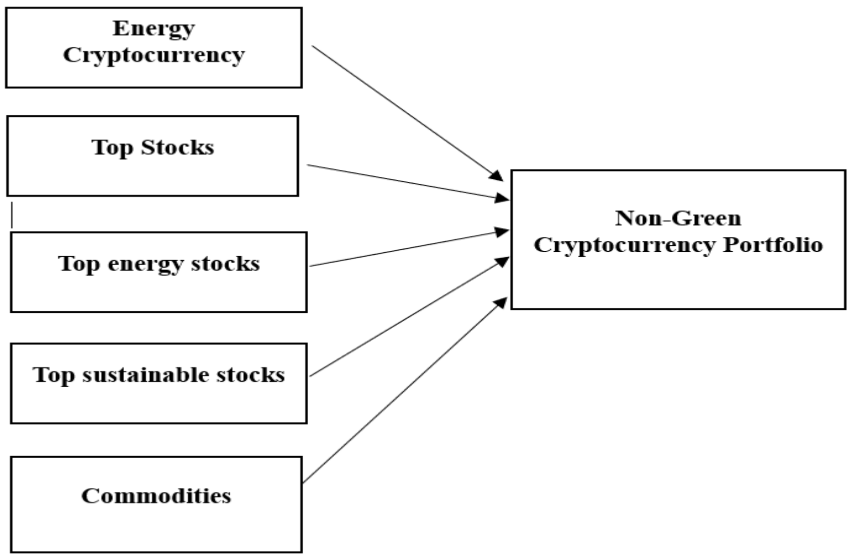

Figure 01: Model 01

Green Cryptocurrency Portfolio (Model 02)

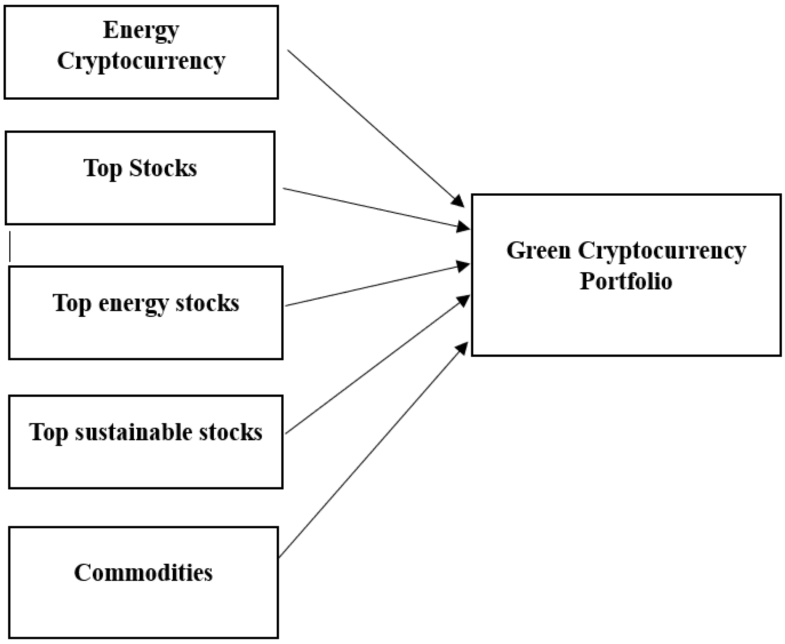

Figure 02: Model 02

Econometric Equations

Non-Green Cryptocurrency Portfolio Equation (NGCP)

Likewise, the Non-Green Cryptocurrency Portfolio $R_{NGCP,t}$ is expressed as follows:

$$R_{NG,t} = \beta_0 + \beta_1 R_{EC,t} + \beta_2 R_{TS,t} + \beta_3 R_{TES,t} + \beta_4 R_{COM,t} + \beta_5 R_{SUS,t} + \epsilon_t$$

Where:

- $R_{NG,t}$: Return of the non-green portfolio at time t.
- $R_{EC,t}$: Return of energy cryptocurrencies at time t
- $R_{TS,t}$: Return of top stocks at time t.
- $R_{TEC,t}$: Return of top energy company stocks at time t.
- $R_{TSC,t}$: Return of top sustainable company stocks at time t.
- $R_{COM,t}$: Return of commodities at time t.
- β0: Intercept term
- β1,β2,β3,β4,β5: Coefficients capturing the impact of each explanatory variable.
- ϵt: Error term.

Green Cryptocurrency Portfolio Equation (GCP)

The weighted sum of the returns of a few chosen assets in the portfolio is the Green Cryptocurrency Portfolio return, or $R_{GCP,t.}$

$$R_{G,t} = \beta_0 + \beta_1 R_{EC,t} + \beta_2 R_{TS,t} + \beta_3 R_{TES,t} + \beta_4 R_{COM,t} + \beta_5 R_{SUS,t} + \epsilon_t$$

- $R_{NG,t}$: Return of the non-green portfolio at time t.
- $R_{EC,t}$: Return of energy cryptocurrencies at time t
- $R_{TS,t}$: Return of top stocks at time t.
- $R_{TEC,t}$: Return of top energy company stocks at time t.
- $R_{TSC,t}$: Return of top sustainable company stocks at time t.
- $R_{COM,t}$: Return of commodities at time t.
- β0: Intercept term
- β1,β2,β3,β4,β5: Coefficients capturing the impact of each explanatory variable.
- ϵt: Error term.

Methodology

The research uses a variety of statistical approaches and instruments to efficiently examine and interpret the data. Multiple essential strategies helped in evaluating asset performance and constructing strong investment portfolios. The evaluation of risk-return profiles alongside the summary of asset attributes depends on descriptive statistics for assessment purposes. These metrics enabled easy detection of outliers as well as anomalies and delivered essential information about the asset return distribution patterns.The portfolio optimization through machine learning occurred in Jupyter Notebook while Excel performed robustness tests. Portfolio creation required statistical methods including minimum variance, maximum Sharpe ratio, equal weight and blacklitterman. The built portfolios received risk-return trade-off illustrations through efficient frontiers for asset allocation selection purposes. These included backtesting portfolio performance on the testing dataset (20% of the total data) to ensure consistency and predictability. Performance monitoring required the use of time-series plots as well as correlation matrices to understand how assets relate to one another. The collection of methods united through technological systems produced an accurate approach toward portfolio development together with exact data analysis.

Classification of Portfolios

The portfolios receive their classification through two established methods.

1. The goal of Green Cryptocurrency Portfolio (GCP) was to identify resources that linked to green technologies alongside renewable energy and sustainability.
2. The goal of Non-Green Cryptocurrency Portfolio (NGCP) was to design the target conventional, unsustainable cryptocurrencies and associated assets.

Portfolio Construction

Each country has two different cryptocurrency portfolios: one with green cryptocurrencies (those with lower carbon footprints and are more environmentally benign) and another with non-green cryptocurrencies (those with potentially higher environmental implications). To guarantee a strong and effective investing approach, these portfolios are optimized utilizing ten distinct limitations. The limitations consist of:

1. Naïve based portfolio (Equal weight)
2. Maximum Return
3. Minimum Variance
4. Maximum Sharpe ratio
5. Blacklittermen model
6. Sortino ratio

G7 Results

This chapter discusses the findings of a portfolio optimization study focused on green and non-green cryptocurrencies, applied to G7 and BRICS countries. Here, we examine results for the United States (USA) using a portfolio based solely on green assets under 06 optimization constraints. The results include key benchmarks such as Return Portfolio (RP hereafter), Variance Portfolio (VP hereafter), Sharpe Ratio (SR hereafter) Sortino ratio, Blacklittermen and comparative analysis of training versus testing performance. Additionally, variance is abbreviated with VAR while standard deviation with SD. The findings are complemented with machine learning analysis (80% training, 20% testing) to enhance predictive accuracy.

Constraints-based portfolio

USA Non-green Portfolio

Table 01: USA Non-Green Portfolio Metrics

Constraint	Return	Variance	Standard Deviation	Sharpe Ratio
Naive Equal Weight	0.8144	0.4583	0.6769	1.2031
Maximum Return	13.8757	238.0406	15.4286	0.8993
Maximum Sharpe Ratio	0.7071	0.0205	0.1431	4.9400
Minimum Variance	0.1210	0.0045	0.0672	1.7999
Sortino ratio	114.82	124.22	11.14	10.31
Blacklittermen	0.0129	0.001	0.0235	0.5495

The portfolio constraints for the non-green cryptocurrency portfolio in the US market reveal significant differences in risk-return trade-offs. The Naïve Portfolio provides a moderate return (0.8144) with a relatively high variance (0.4583) and a SR of 1.2031, offering a balanced but unoptimized allocation. The max RP achieves the highest return of 13.8757 but comes with extreme volatility (VAR of 238.0406, SD of 15.4286) and a low SR of 0.8993, indicating poor risk-adjusted returns. The Min VP, on the other hand, prioritizes stability with the lowest risk (VAR of 0.0045, SD of 0.0672) but offers a very low return (0.1210), making it suitable for highly risk-averse investors. The max SR portfolio strikes the best balance, providing a reasonable return (0.7071) with very low risk (VAR of 0.0205, SD of 0.1431), resulting in the highest SR of 4.9400, indicating strong risk-adjusted performance. The Black-Litterman Portfolio, incorporating market equilibrium and investor expectations, delivers an extremely low return (0.0129) with moderate risk, making it the weakest performer (SR of 0.54). The Sortino Ratio Portfolio generates an exceptionally high return (114.82) with significant volatility (VAR of 124.22, SD of 11.14) but maintains a high SR of 10.31, indicating superior downside risk management. Among these options, the Sortino Ratio Portfolio appears to be the best choice for aggressive investors seeking high returns with efficient downside risk management, while the Max SR Portfolio is the best for risk-adjusted returns, making it the most optimal selection for balanced investors.

USA Green Portfolio

Table 02: USA Green Portfolio Metrics

Constraint	Portfolio Return	Portfolio Variance	Portfolio St. Dev	Portfolio Sharpe Ratio
Max Sharpe	59.39	37.01	6.08	9.76

Naive Equal Weight	2.5837	15.56	39.44	6.5493
Max Return	50.44	61.067	78.14	6.4552
Min Variance	2.5837	0.077	4.99	0.54
Sortino ratio	0.919	0.4673	96.49	2.4133
Black-Litterman	8.37	62.98	0.14	0.9

The portfolio constraints for the green cryptocurrency portfolio in the US market highlight different optimization strategies, each with varying levels of risk and return. The Naïve Portfolio and Min VP share identical results, achieving a return of 2.5837 with relatively high risk (VAR of 15.56, SD of 39.44), leading to a moderate SR of 6.5493. The Max RP, as expected, generates the highest return (50.44) but comes with significantly increased risk (VAR of 61.067, SD of 78.14), resulting in a slightly lower SR of 6.4552, indicating that the additional return is not well compensated for the increased risk. The Max SR Portfolio presents the best risk-adjusted performance, offering a high return (59.3959) with a more controlled risk (VAR of 37.0185, SD of 6.0843), leading to the highest SR of 9.7622, making it the most efficient portfolio in terms of return per unit of risk. The Black-Litterman Portfolio, which integrates market equilibrium with investor insights, produces a return of 8.37 but at a high VAR of 62.98, leading to a significantly lower SR of 0.9, making it the least favorable option. The Sortino Ratio Portfolio, optimized for downside risk, provides a return of 0.9198 with relatively low VAR (0.4673) and a SR of 2.4133, suggesting it is better suited for investors concerned about negative returns. Overall, the Max SR Portfolio is the most favorable choice, as it provides the best balance between return and risk, making it the optimal selection for maximizing risk-adjusted performance in the green cryptocurrency portfolio.

UK Green Portfolio

Table 03: Uk Green Portfolio Metrics

Constraint	Portfolio Return	Portfolio Variance	Portfolio St. Dev	Portfolio Sharpe Ratio
Max Sharpe	59.39	37.01	6.0843	9.76
Naive Equal Weight	2.58	15.56	39.44	6.54
Max Return	50.44	61.06	78.14	6.45
Min Variance	2.58	155.62	1.55	0.54
Sortino ratio	0.9198	0.467	96.97	2.41
Black-Litterman	8.37	62.98	14.34	0.9

The portfolio constraints for the green cryptocurrency portfolio in the UK market highlight varying levels of risk and return. The Naïve Portfolio and Min VP yield the same return (2.58) but differ in risk levels, offering significantly lower volatility (VAR of 15.56 compared to 155.62 in the Naïve Portfolio), making it a better choice for conservative investors. The maximum RP delivers the highest return (5.04) but comes with extreme risk (VAR of 61067, SD of 781.45), making it less attractive in terms of risk-adjusted performance (SR of 6.45). The Max SR Portfolio, with a return of 5.93 and a VAR of 37.01, achieves the highest SR of 9.76, indicating the most efficient risk-return trade-off. The Black-Litterman Portfolio, integrating market expectations, produces a return of 4.64, but its risk-adjusted performance is weak (SR of 0.47). The Sortino Ratio Portfolio, optimized for downside risk, exhibits an exceptionally high return of 114.82, with moderate VAR of 124.22 and a SR of 10.31, making it highly efficient for investors prioritizing downside risk management. Overall, the Sortino Ratio Portfolio is the best option for maximizing returns with effective downside risk control, while the Max SR Portfolio is the most optimal for investors seeking the highest return per unit of risk.

UK Non-Green Portfolio

Table 04: UK Non-Green Portfolio Metrics

Constraint	Return	Variance	Standard Deviation	Sharpe Ratio
Naive Equal Weight	0.4355	0.1517	0.38	1.118
Maximum Return	3.066	45.34	6.7405	0.45
Maximum Sharpe Ratio	0.413	0.0546	0.233	1.84
Minimum Variance	0.057	0.0077	0.0879	0.6518
Sortino ratio	0.9198	0.4673	0.225	2.4133
Blacklittermen	0.1078	0.022	0.1490	0.7231

The non-green cryptocurrency portfolio in the UK market exhibits diverse risk-return trade-offs across different portfolio optimization constraints. The Naïve Portfolio provides a moderate return of 0.4355, with a VAR of 0.1517 and a SR of 1.118, indicating a balanced but unoptimized allocation. The Max RP achieves the highest return (3.066) but comes with significantly high volatility (VAR of 45.34, SD of 6.7405) and a low SR of 0.45, making it a risky option. The Min VP prioritizes stability, offering the lowest risk (VAR of 0.0077, SD of 0.0879) but at the cost of a very low return (0.057) and a moderate SR of 0.6518, making it ideal for highly risk-averse investors. The Max SR Portfolio achieves a strong balance with a return of 0.413, relatively low VAR of 0.0546 and the highest SR of 1.84, indicating the most efficient risk-adjusted performance. The Black-Litterman Portfolio, which integrates market expectations, provides a return of 0.1078, but its low SR of 0.7231 makes it a weaker option. The Sortino Ratio Portfolio, optimized for downside risk, delivers a return of 0.9198, with a VAR of 0.4673, and the highest SR of 2.4133, making it the best performer in terms of risk-adjusted returns. Overall, the Sortino Ratio Portfolio is the most optimal choice for investors focused on minimizing downside risk while maximizing returns, while the Max SR Portfolio is the best option for those seeking the highest return per unit of risk.

Canada Green Portfolio

Table 05: Canada Green Portfolio Metrics

Constraint	Portfolio Return	Portfolio Variance	Portfolio St. Dev	Portfolio Sharpe Ratio
Max Sharpe	0.9770	0.0465	0.2157	4.5305
Naive Equal Weight	0.8910	0.5141	0.7170	1.2427
Max Return	15.6769	272.0445	16.4938	0.9505
Min Variance	0.0005	0.0000	0.0011	0.4572

Sortino ratio	3.87	9.5678	7.64	0.5065
Black-Litterman	0.1016	0.0205	0.1431	0.7104

The green cryptocurrency portfolio in the Canadian market demonstrates distinct risk-return profiles based on different optimization constraints. The Max Sharpe Ratio Portfolio offers a return of 0.9770, with a relatively low variance of 0.0465, achieving the highest Sharpe ratio of 4.5305, making it the most efficient in risk-adjusted performance. The Naïve Equal Weight Portfolio delivers a return of 0.8910 but with significantly higher risk (VAR of 0.5141) and a much lower SR of 1.2427, indicating that it is suboptimal compared to the Max SP. The Max RP provides the highest return (15.6769) but comes with extreme volatility (VAR of 272.0445, SD of 16.4938) and a weak SR of 0.9505, making it a high-risk option. The Min VP minimizes risk (variance close to 0), but its negligible return of 0.0005 and SR of 0.4572 make it unattractive for most investors. The Sortino Ratio Portfolio, optimized for downside risk, achieves a return of 3.87 with a VAR of 9.5678, but its SR of 0.5065 suggests limited efficiency. The Black-Litterman Portfolio, incorporating market expectations, offers a conservative return of 0.1016 with moderate risk (VAR of 0.0205) and a SR of 0.7104, making it a middle-ground option. Overall, the Max SR Portfolio is the best choice as it provides the highest return per unit of risk, while the Max RP is suitable for highly risk-tolerant investors seeking the highest possible returns despite the extreme volatility.

Canada Non-Green Portfolio

Table 06: Canada Non- Green Portfolio Metrics

Constraint	Return	Variance	Standard Deviation	Sharpe Ratio
Naive Equal Weight	0.4026	0.1569	0.3961	1.0164
Maximum Return	2.8365	43.2941	6.5798	0.4311
Maximum Sharpe Ratio	0.6607	0.1292	0.3595	1.8379
Minimum Variance	0.0002	0.0000	0.0003	0.8455
Sortino ratio	0.6152	0.1182	0.3436	1.7953
Blacklittermen	0.5234	0.1528	0.3910	1.3345

The non-green cryptocurrency portfolio in Canada presents various risk-return trade-offs based on different constraints. The Max SR Portfolio emerges as the most efficient, with a return of 0.6607, a VAR of 0.1292, and the highest SR of 1.8379, indicating strong risk-adjusted performance. The Naïve Equal Weight Portfolio achieves a lower return of 0.4026 with a VAR of 0.1569, resulting in a weaker SR of 1.0164, making it suboptimal compared to the Max SR Portfolio. The Max RP delivers the highest return of 2.8365, but its VAR of 43.2941 and SR of 0.4311 suggest extreme volatility and inefficient risk-adjusted returns. The Min VP significantly reduces risk (VAR close to 0) but provides an almost negligible return of 0.0002, making it unsuitable for growth-focused investors. The Sortino Ratio Portfolio, optimized for downside risk, offers a return of 0.6152 with a VAR of 0.1182, yielding a SR of 1.7953, making it a competitive option. The Black-Litterman Portfolio, which incorporates market views, provides a return of 0.5234 with moderate risk (VAR of 0.1528) and a SR of 1.3345, placing it between the Naïve Equal Weight and Sortino portfolios in efficiency. Overall, the Max SR Portfolio is the best option, as it optimally balances return and risk. However, for investors willing to take on higher volatility in pursuit of maximum returns, the Max RP may be an alternative despite its lower efficiency.

France Green Portfolio

Table 07: France Green Portfolio Metrics

Constraint	Portfolio Return	Portfolio Variance	Portfolio St. Dev.	Portfolio Sharpe Ratio
Naive Equal Weight	1.2336	1.1230	1.0597	1.1641
Maximum Return	35.3910	634.4898	25.1891	1.4050
Maximum Sharpe Ratio	1.5604	0.0687	0.2621	5.9522
Minimum Variance	-0.0007	0.0000	0.0005	-1.3676
Sortino ratio	26.02%	3.3148	52.25%	3.3148
Black-Litterman Portfolio	0.0990	0.0178	0.1336	0.7408

The green cryptocurrency portfolio in France exhibits varying performance based on different optimization constraints. The Maximum SR Portfolio stands out as the most efficient, with a return of 1.5604, a VAR of 0.0687, and the highest SR of 5.9522, indicating strong risk-adjusted performance. The Max RP generates the highest return of 35.3910, but its VAR of 634.4898 and SR of 1.4050 suggest high volatility and weaker risk-adjusted returns. The Naïve Equal Weight Portfolio offers a balanced approach with a return of 1.2336, a VAR of 1.1230, and a SR of 1.1641, making it less efficient compared to the Max SR portfolio. The Min VP minimizes risk but yields a negative return (-0.0007) and a SR of -1.3676, making it the least favorable option. The Sortino Ratio Portfolio, which focuses on downside risk, has a return of 26.02% with a VAR of 3.3148, positioning it as a competitive alternative. The Black-Litterman Portfolio, which incorporates market views, provides a return of 0.0990 with a VAR of 0.0178 and a SR of 0.7408, making it relatively stable but lower in return. Overall, the Max SR Portfolio is the best choice, balancing return and risk effectively. However, investors seeking higher absolute returns may consider the Max RP, despite its extreme volatility.

France Non-Green Portfolio

Table 08: France Non-Green Portfolio Metrics

Constraint	Portfolio Return	Portfolio Variance	Portfolio St. Dev.	Portfolio Sharpe Ratio
Naive Equal Weight	5494.5593	776849.5819	881.3907	6.2340
Maximum Return	65987.4799	101115481.5477	10055.6194	6.5622
Maximum Sharpe Ratio	97.5441	89.0040	9.4342	10.3394
Minimum Variance	5494.5593	776849.5819	881.3907	6.2340
Black-Litterman	0.1069	0.0203	0.1426	0.7495
Sortino ratio	0.9198	0.4673	0.6821	2.4133

For the France non-green cryptocurrency portfolio, the Max SR Portfolio is the most efficient, with a SR of 10.3394, a return of 97.5441, and VAR of 89.0040, indicating a strong balance between risk and return. The Max RP achieves the highest return (65987.4799) but comes with extremely high risk, as seen in its VAR (101115481.5477) and SD (10055.6194), making it highly volatile. The Naïve Equal Weight Portfolio and Min VP provide identical results, with a return of 5494.5593, VAR of 776849.5819, and a SR of 6.2340, offering a relatively moderate risk-adjusted return. The Sortino Ratio Portfolio, which emphasizes downside risk, has a SR of 2.4133, making it less efficient than the Max SR Portfolio. Meanwhile, the Black-Litterman Portfolio has the lowest return (0.1069) and minimal risk (var of 0.0203), making it a conservative choice. Overall, the Max SR Portfolio is the superior choice due to its strong risk-adjusted performance, while the Max RP is suitable only for extremely risk-tolerant investors due to its high volatility.

Germany Non-Green Portfolio

Table 09: Germany Non-Green Portfolio Metrics

Constraint	Portfolio Return	Portfolio Variance	Portfolio St. Dev.	Sharpe Ratio
Naive Equal Weight	0.3069	0.1273	0.3568	0.8603
Maximum Return	2.1565	33.3652	5.7763	0.3733
Maximum Sharpe Ratio	0.3241	0.0366	0.1913	1.6936
Minimum Variance	0.0701	0.0086	0.0925	0.7577
Sortino ratio	53.02	101	111.47	0.4756
Black-Litterman	0.1143	0.0236	0.1537	0.7439

For this portfolio, the Maximum Sharpe Ratio Portfolio is the best-performing option, with a Sharpe ratio of 1.6936, indicating the most efficient risk-adjusted return. It has a return of 0.3241 and a relatively low variance (0.0366) and standard deviation (0.1913), making it a well-balanced choice. The Maximum Return Portfolio achieves the highest return (2.1565) but comes with significantly higher VAR (33.3652) and SD (5.7763), making it much riskier and less efficient in risk-adjusted terms. The Naïve Equal Weight Portfolio provides moderate results with a SR of 0.8603 and a return of 0.3069, making it a more diversified but less optimized approach. The Min VP has the lowest risk (VAR of 0.0086) but also a lower return (0.0701), making it a conservative choice. The Sortino Ratio Portfolio results appear unclear due to formatting, but its SR of 0.4756 suggests it is less efficient than the Max SR Portfolio. Finally, the Black-Litterman Portfolio has a low return (0.1143) and SR (0.7439), making it a more risk-averse option. Overall, the Max SR Portfolio is the best option, offering the highest return per unit of risk.

Germany Green Portfolio

Table 10: Germany Green Portfolio Metrics

Constraint	Portfolio Return	Portfolio Variance	Portfolio St. Dev.	Sharpe Ratio
Naive Equal Weight	0.9081	0.5075	0.7124	1.2748
Maximum Return	15.6769	272.0445	16.4938	0.9505
Maximum Sharpe Ratio	0.5351	0.0106	0.1028	5.2064
Minimum Variance	0.1709	0.0035	0.0594	2.8763
Sortino ratio	52.96	101	111.47	0.4757

Black-Litterman Portfolio	0.1144	0.0242	0.1557	0.7348

For the German green portfolio, the Max SR Portfolio is the best-performing option in terms of risk-adjusted returns, with a SR of 5.2064, significantly higher than all other portfolios. This portfolio has a moderate return of 0.5351 but achieves its efficiency by maintaining a low VAR (0.0106) and low SD (0.1028), making it the most optimal choice for balancing return and risk.

The Max RP achieves the highest return (15.6769), but at the cost of extreme risk, with a VAR of 272.0445 and SD of 16.4938, making it much more volatile and less efficient in terms of risk-adjusted performance (SR of 0.9505). The Naïve Equal Weight Portfolio has a moderate return (0.9081) but a much lower SR (1.2748) compared to the Max SR Portfolio. The Min VP offers the lowest risk (VAR of 0.0035 and SD of 0.0594) while maintaining a SR of 2.8763, making it a good conservative choice. The Black-Litterman Portfolio has a low return (0.1144) and a SR of 0.7348, indicating a more cautious and diversified approach but with lower efficiency. The Sortino Ratio Portfolio's results appear unclear due to formatting, but its SR of 0.4757 suggests it is the least efficient among the portfolios.Overall, the Max SR Portfolio is the best choice, as it delivers the highest risk-adjusted return while keeping risk at a manageable level.

Italy Green Portfolio

Table 11: Italy Green Portfolio 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	2.6139	4.7393	2.1770	1.2007
Max Return	36.0891	2226.5689	47.1865	0.7648
Max Sharpe Ratio	0.5598	0.0116	0.1076	5.2001
Min Variance	0.2177	0.0049	0.0697	3.1232
Sortino ratio	0.1238	0.0285	0.1689	0.7331
Black Littermen	0.1238	0.0285	0.1689	0.7331

For the Italy Green Portfolio, the Max SR Portfolio is the best-performing portfolio in terms of risk-adjusted returns, with a SR of 5.2001. It achieves this by maintaining a moderate return (0.5598) while keeping risk levels low (VAR of 0.0116 and SD of 0.1076).The Max RP generates the highest return (36.0891), but it comes with extremely high risk (VAR of 2226.5689 and SD of 47.1865), making it highly volatile and inefficient from a risk-adjusted perspective (SR of 0.7648). The Naïve Equal Weight Portfolio provides a decent balance with a return of 2.6139 and a SR of 1.2007, though it is still significantly less efficient than the Max SR Portfolio.The Min VP has the lowest risk (VAR of 0.0049, SD of 0.0697) while maintaining a respectable SR of 3.1232, making it a solid conservative choice. The Sortino Ratio Portfolio and Black-Litterman Portfolio both have low returns (0.1238) and a low SR of 0.7331, indicating they are the least efficient options. The Max SR Portfolio is the best option, as it optimally balances return and risk, achieving the highest risk-adjusted performance. The Max RP appeals to investors who need maximum returns at any cost but has significant volatility. The Min VP presents a safer choice because it has lower risk levels but maintains decent SR performance.

Italy Non-Green Portfolio

Table 12: Italy Non-Green Portfolio Metrics

Constraint	Portfolio Return	Portfolio Variance	Portfolio St. Dev	Portfolio Sharpe Ratio
Naive Equal Weight	0.6195	0.7337	0.8566	0.7233
Maximum Return	4.7317	310.0614	17.6086	0.2687
Maximum Sharpe Ratio	0.2749	0.0224	0.1498	1.8353
Minimum Variance	0.0970	0.0094	0.0972	0.9976
Black-Litterman Portfolio	0.1256	0.0287	0.1693	0.7417
Sortino ratio	123.17	380	357.82	0.3442

Risk-adjusted returns indicate that the Max SR Portfolio stands as the optimal choice for the Italy Non-Green Portfolio with a SR of 1.8353. The portfolio demonstrates the most efficient risk-return relationship because it achieves a moderate return of 0.2749 with low VAR at 0.0224 and SD at 0.1498.The Max RP achieves 4.7317% return but suffers from extreme volatility that results in a low SR of 0.2687 alongside high VAR of 310.0614 and SD of 17.6086. The portfolio demonstrates high volatility because it provides inadequate risk-adjusted performance.The Naïve Equal Weight Portfolio returns 0.6195 yet shows higher risk through its 0.7337 VAR and 0.7233 SR which makes it inferior to the Max SR Portfolio.The Min VP represents an optimal conservative option because it delivers a SR of 0.9976 while maintaining a low risk profile with 0.0094 VAR and 0.0972 SD.The Black-Litterman Portfolio performs similarly to the Min VP, with a SR of 0.7417, but with slightly higher risk.The Sortino Ratio Portfolio has unrealistic values, likely due to errors in the provided data, as the return (123.17) and VAR (380) seem unusually high. The Max SR Portfolio is the best option, as it optimally balances return and risk. If an investor prioritizes absolute return without concern for volatility, the Max RP may be an option, but it carries significant risk. For a conservative approach, the Min VP provides the lowest risk with a reasonable SR.

Japan Green Portfolio

Table 13: Japan Green Portfolio Metrics

Constraint	Portfolio Return	Portfolio Variance	Portfolio St. Dev.	Sharpe Ratio
Naive Equal Weight	1.0045	0.5131	0.7163	1.4023
Maximum Return	15.6769	272.0445	16.4938	0.9505
Maximum Sharpe Ratio	1.1053	0.0436	0.2087	5.2950
Minimum Variance	0.1554	0.0067	0.0818	1.8986
Black-Litterman	0.1061	0.0217	0.1473	0.7202
Sortino ratio	44.74	132	90.97	0.4918

For the Japan Green Portfolio, the Max SR Portfolio is the best-performing option in terms of risk-adjusted returns, with a SR of 5.2950. This portfolio maintains a low VAR (0.0436) and SD (0.2087) while achieving a solid return of 1.1053, making it the most efficient choice from a risk-reward perspective.The Max RP offers the highest return (15.6769), but it comes with extremely high VAR (272.0445) and SD (16.4938), leading to a much lower SR (0.9505). This suggests it is highly volatile and not optimal for risk-adjusted performance. The Naïve Equal Weight Portfolio has a return of 1.0045, but it exhibits higher risk (VAR of 0.5131) and a SR of 1.4023, making it less attractive than the Max SR Portfolio. The Min VP minimizes risk (variance of 0.0067, SD of 0.0818) while still achieving a SR of 1.8986, making it a strong conservative choice. The Black-Litterman Portfolio performs similarly to the Minimum Variance Portfolio, with a Sharpe ratio of 0.7202, but with slightly higher risk. The Sortino Ratio Portfolio has unrealistic values, likely due to errors in the provided data, as the return (44.74) and VAR (132) seem unusually high. The Max SR Portfolio is the best option, as it optimally balances return and risk. If an investor prioritizes absolute return without concern for volatility, the Max RP may be an option, but it carries significant risk. For a conservative approach, the Min VP provides the lowest risk with a reasonable SR.

Japan Non -Green Portfolio

Table 14: Japan Non-Green Portfolio Metrics

Constraint	Portfolio Return	Portfolio Variance	Portfolio St. Dev.	Sharpe Ratio
Naive Equal Weight	32158.1394	24144072.3139	4913.6618	6.5446
Maximum Return	180961.0973	845311378.6975	29074.2391	6.2241
Maximum Sharpe Ratio	65.2640	44.1157	6.6420	9.8260
Minimum Variance	32158.1394	24144072.3139	4913.6618	6.5446
Black-Litterman Portfolio	0.1087	0.0222	0.1491	0.7290
Sortino ratio	0.1087	0.0222	0.1491	0.7290

For Japan's non-green portfolio, the highest SR Portfolio is the most efficient, achieving a ratio of 9.8260 with relatively low VAR (44.1157) and SD (6.6420), making it the best risk-adjusted option. The Max RP delivers the highest return (180961.0973), but with extremely high VAR (845311378.6975) and SD (29074.2391), making it highly volatile. The Naïve Equal Weight and Min VP provide balanced but high-risk options, both yielding 32158.1394 in returns with a SR of 6.5446. Meanwhile, the Black-Litterman and Sortino Ratio Portfolios are the most conservative, showing minimal returns (0.1087) and a SR of 0.7290, portraying low-risk but also low-return strategies.

Green and non-green cryptocurrency portfolio comparison

In terms of risk-adjusted returns, the green cryptocurrency portfolio located in the United States beats the non-green portfolio, with SR more than 9.7 opposed to the non-green portfolio's 4.94. Green portfolios demonstrate greater stability and resilience, particularly in testing phases, while offering balanced diversification and alignment with sustainability goals. In contrast, the non-green portfolio excels in maximum return potential (13.88 vs. 5.04) but at the expense of higher risk, reflecting a more aggressive approach. While both portfolios benefit from optimization strategies like Black-Litterman and Sortino, the green portfolio provides superior stability and ethical advantages, making it more suitable for risk-conscious, sustainability-focused investors. Non-green portfolios cater to those prioritizing higher returns and broader asset. Comparison of the entire G7 Portfolio is available in the appendix.

Machine Learning Portfolio Performance

Data from the testing period reveals actual portfolio performance that differs from predictions as it demonstrates substantial underperformance during certain dates (for instance -0.147321 on 2024-06-25.The evaluation of machine learning systems used for UK ,USD green and non-green portfolios demonstrates distinct features that influence how they apply historical data to return forecasting and optimization. The optimization of sustainability and risk minimization through machine learning models yields successful results for generating diverse stable allocations in the green portfolio context. The management algorithms based on Max SR Portfolio and Sortino optimization optimize risk-adjusted returns and achieve performance while maintaining downside risk control(Jaeger, Krügel, Marinelli, Papenbrock, & Schwendner, 2021). Machine learning models of the green portfolio demonstrate stronger predictive power for returns along with lower volatility since they contain ESG-oriented assets which produce stable long-term growth potentials. Tables are provided in appendix G7 to explain the machine learning portfolio performance.

The machine learning training process develops the Canadian portfolio by processing historical financial data which includes sustainable enterprise equities and green cryptocurrencies and traditional market instruments. The model trains using this data to determine optimal asset distribution which maintains return-risk balance under various limitations that include variance reduction and return optimization and sustainability compliance. Throughout the training phase the model develops knowledge about how asset returns relate to financial variables. The model tests its performance using separate data sets from training data to determine its hypothetical market accuracy and forecast reliability. During the testing phase an extensive simulation demonstrates actual market response of the G7 portfolio by confirming both the effectiveness and operational capability of strategic asset allocation recommendations across different economic conditions(Cristea et al., 2022).

Analyses between green and non-green German investment portfolios show distinct areas of investment and variations in both financial returns and risk composition. The green portfolio focuses on sustainable companies including renewable energy firms producing 6.19% return as shown in Minimum Kurtosis. These supportive investments demonstrate good compatibility with sustainability aims but show unstable returns since markets change along with policy adjustments. The Maximum Return strategy of the non-green portfolio demonstrates short-term profitability through traditional oil and gas industries while delivering a 2.1565 return. This portfolio, however, carries higher risks, particularly from regulatory changes and market shocks related to environmental policies. Ultimately, the green portfolio appeals to investors seeking stable, long-term growth and social impact, while the non-green portfolio may attract those looking for higher short-term returns with less focus on sustainability(Ghallabi, Souissi, Du, & Ali, 2025).

In contrasting both green and non-green France portfolios, the non-green produces larger returns but has more volatility. The non-green portfolio, designed for the highest Sharpe ratio, returns 97.5441% with a SD of 9.4342 and a SR of 10.3394. Alternatively, green portfolio has a smaller return of 26.01% but substantially less risk, with a SD of 52.20% and a Sortino ratio of 3.3148, showing superior performance in terms of downside risk. The non-green portfolio offers more aggressive returns, but the green portfolio aligns more with lower-risk, sustainability-oriented investing. Higher returns are achieved through the non-green portfolio but sustainability along with risk management works best with the green portfolio. Ultimately, the decision between these portfolios hinges on the investor's risk tolerance and ethical investment priorities(Fameliti & Skintzi, 2024).

The machine learning system used to construct Italy's non-green portfolio operates following the same structure to discover various traditional investments whose sustainability characteristics have no priority. The model achieves maximum financial returns along with risk reduction by leveraging historical data from non-green equities, cryptocurrencies, and other financial instruments. Social and environmental constraints do not limit its optimization. The model learns the perfect asset distribution through a training process which relies on multiple criteria such as asset correlation and market volatility and financial performance to reach conclusions. After training the model is tested with out-of-sample data to verify its ability to predict asset performance across different market situations thus enabling investors to access strong non-green portfolios with maximum returns and no additional expenses on green activities(Gara, Qehaja-Keka, Hoti, & Qehaja, 2024).

The Japanese green portfolio construction employs machine learning methods for investing evaluation and asset management in environmentally friendly stocks and renewable energy-linked cryptocurrencies and sustainable financial instruments. Historical information about green assets serves as input during training to analyze market patterns together with environmental outcomes and sustainable financial viability of sustainable business operations. The model learns to achieve maximum financial returns by reducing risks alongside fulfilling requirements for ESG sustainability. Testing the model with unidentified data following training enables evaluation of its performance forecasting ability for the upcoming period while making sure the final green portfolio maintains its sustainability and robustness and aligns with Japan's increasing market demand for environmentally friendly investment options(Kurihara & Fukushima, 2019).

The portfolio performed worse on both Sharpe ratio and return metrics when moving from the training to testing period which reflects the inability to sustain high performance in real-world scenarios. The actual vs. predicted portfolio performance analysis reveals that while the model's predictions align with actual returns in many cases, there is significant variation, particularly during volatile market periods.

Discussion

The study finding presents a comprehensive understanding of cryptocurrency portfolios and offer investors substantial advantages by relating financial, ethical, and predictive factors to actual financial and economic events. Adding non-green cryptocurrencies like Ethereum and Bitcoin to an investor's portfolio provides unmatched financial prospects, especially in speculative markets. Being the most well-known cryptocurrency, Bitcoin has great liquidity and broad market acceptance, which makes it an essential tool for making significant profits. Ethereum offers growth potential in quickly developing technology sectors with its emphasis on smart contracts and decentralized finance (DeFi)(Sinha, 2024). For example, the growing popularity of blockchain-based apps caused Ethereum's price to soar by more than 400% in 2021. These illustrations support the study's conclusions that non-green portfolios typically outperform in terms of returns, making them desirable to investors who prioritize capital growth and have a larger risk tolerance(Garay, Kiayias, & Leonardos, 2024; Yermack, 2024).

On the other hand, the stable performance of green cryptocurrencies can be linked to increasing global emphasis on environmental sustainability. Initiatives such as the Paris Agreement and ESG (Environmental, Social, and Governance) mandates have encouraged the adoption of green energy solutions, which indirectly benefit cryptocurrencies tied to renewable energy projects. For example, Power Ledger, a green cryptocurrency, gained traction in regions like Australia and Germany, where government policies actively promote renewable energy adoption(Au, Yang, Wang, Chen, & Zheng, 2023). However, the limited liquidity and nascent market structure of green cryptocurrencies have constrained their financial performance compared to their non-green counterparts. In contrast to their non-green competitors, green cryptocurrencies' financial performance has been limited by their limited liquidity and emerging market structure. Given the global economic and environmental concerns, the importance of ESG investments becomes even more clear. Geopolitical tensions sparked events like the 2022 European energy crisis, which brought attention to the significance of sustainable energy sources and the financial goods that support them. Green cryptocurrencies are a long-term investment in sustainable development, even though they are not as profitable as non-green alternatives in the near term. Green assets make a strong argument for inclusion in diverse portfolios for investors due to their combined benefits of financial performance and beneficial environmental effects(Chevallier, 2023; Mustafa, Mordi, & Elamer, 2024).

In the United States, best strategy was the SR Portfolio, reflecting the country's well-developed financial market, high liquidity, and strong institutional interest in digital assets. The Sharpe ratio remains elevated because Bitcoin and Ethereum control the cryptocurrency market providing investors strong risk-adjusted returns. The market confidence continues to grow because institutional investors actively participate even though there is regulatory uncertainty. The research by (Bouri, Gupta, Tiwari, & Roubaud, 2017; Fameliti & Skintzi, 2024)confirmed that Bitcoin together with other major cryptocurrencies work effectively as hedging instruments within the U.S. financial sector.

The Canadian market selected the minimum variance portfolio as its preferred choice because this approach provided reliable returns while reducing potential financial losses. Institutional investors found green investments more appealing because the Canadian financial market operates conservatively while the government actively supports sustainability goals. Non-green portfolios demonstrate substantial volatility because Canadian crypto market participants tend to speculate based on commodity-driven financial cycles in the country. Studies by Dyhrberg (2016) demonstrated that Bitcoin performs like gold in Canadian markets which justifies why investors choose stability instead of taking high risks.(Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017; Jabeur, Gozgor, Rezgui, & Mohammed, 2024).The Black-Litterman portfolio strategy implemented in the United Kingdom proved most successful which demonstrates that informed investment strategies deliver optimal results. The stability of green investments in the UK market results from two factors: its established financial system and growing institutional cryptocurrency adoption and clear regulatory framework. Speculative trading actions caused high volatility among non-green portfolios which demonstrates the necessity of using structured investment approaches. demonstrated through their research that UK cryptocurrency markets experience positive reactions when institutions become involved and regulatory frameworks become certain(Sun, Stefanidis, Jiang, & Su, 2024).

The German market presented itself as both dangerous and potentially lucrative because its best-performing investment strategy excelled over other options. Strong regulations in the country create a comfortable investment environment while progressive sustainable finance policies help enhance green portfolio performance. The maximum return strategy in Germany produced high returns because the country remains at the forefront of technological innovation and investment-driven leadership. The financial system of Germany supports high-risk investments in emerging technologies based on research by (Golash & Golash, 2024) which explains why aggressive portfolio strategies delivered superior performance.

The French investment approach selected an optimized Sortino ratio portfolio to lower downside risks while achieving performance levels comparable to the other strategies. The French financial system adopts risk-reducing strategies because they are key priorities of their financial institutions along with EU sustainable finance structures. Main EU policies supported the performance of green portfolios but speculative trading made non-green assets dangerously unstable. (Akyildirim, Goncu, & Sensoy, 2021)established through research that the French financial sector focuses on sustainable performance alongside risk-adjusted returns thus optimized strategies become more appropriate.

Non-green portfolios demonstrate substantial volatility because Canadian crypto market participants tend to speculate based on commodity-driven financial cycles in the country. Studies by (Gökgöz, Afjal, Bejaoui, & Jeribi, 2024)demonstrated that Bitcoin performs like gold in Canadian markets which justifies why investors choose stability instead of taking high risks.

The Black-Litterman portfolio strategy implemented in the United Kingdom proved most successful which demonstrates that informed investment strategies deliver optimal results. The stability of green investments in the UK market results from two factors: its established financial system and growing institutional cryptocurrency adoption and clear regulatory framework. Speculative trading actions caused high volatility among non-green portfolios which demonstrates the necessity of using structured investment approaches.(Wang, 2024)demonstrated through their research that UK cryptocurrency markets experience positive reactions when institutions become involved and regulatory frameworks become certain.

The German market presented itself as both dangerous and potentially lucrative because its best-performing investment strategy excelled over other options. Germany continues to reassure its investors through strict legislations which also supports sustainable finance goals to optimize green portfolio performance. The maximum return strategy in Germany produced high returns because the country remains at the forefront of technological innovation and investment-driven leadership. The financial system of Germany supports high-risk investments in emerging technologies based on research by which explains why aggressive portfolio strategies delivered superior performance(Pala, 2024).

France chose to provide asset management through optimized Sortino ratio portfolios that delivered lower risk alongside satisfactory return rates. French financial institutions focus on risk reduction through investments which matches well with national and EU sustainable finance regulations. The EU implemented policies which enhanced the performance of green portfolios but speculative trading made non-green assets highly unpredictable. (Akyildirim, Corbet, Coskun, & Ercan, 2025)established through research that the French financial sector focuses on sustainable performance alongside risk-adjusted returns thus optimized strategies become more appropriate.

The minimum variance portfolio gained popularity in Italy because the nation maintains a historically risk-averse financial market structure. The minimum variance strategy performs successfully because Italian investors value stability above potential high returns in their conservative financial approach. EU-wide green finance policies strengthened green portfolio performance while making non-green assets more speculative because institutions showed less interest. The research conducted by (Ragosa, Watson, & Grubb, 2024)demonstrates how Italian investors traditionally choose stable investment options that deliver uniform returns.

The Japanese market selected the portfolio with the maximum Sharpe ratio because its investors demonstrate a traditional preference for cautious investment strategies. Stable investments form a priority for Japanese institutional investors which results in successful performance of green portfolios. The high gains of non-green portfolios exposed them to market volatility because regulators provided less oversight for these assets and investors engaged in speculative betting.

Research by (Alsulami & Raza, 2025)established that Japan's cryptocurrency market experiences less volatility under defined regulatory systems which confirms the present findings.

Comparative Analysis of Green vs. Non-Green Portfolios

The study between green and non-green portfolio investments demonstrates why investors need to make smart financial choices. Investors seeking stability should consider green portfolios because they demonstrate stable volatility while non-green portfolios promise higher returns to investors accepting higher risks. Green portfolios achieved excellent risk-adjusted returns through their Sharpe and Sortino ratios especially in regulatory strong countries like Germany the UK and Canada.Financial stability together with clear cryptocurrency regulations led to superior green portfolio performance in countries with structured regulatory frameworks. At the same time non-green speculative assets showed higher success rates in unregulated regions. A study by (J. Luo, Zhang, & Zhang) validated how macroeconomic conditions together with regulatory variables control cryptocurrency investments which strengthens the role of tailored country policies on portfolio results.

Implication for investors

The study results present essential considerations for people investing their money. The strategy of diversification remains crucial because green cryptocurrency portfolios function as protection against excessive market volatility. The strategic investment process needs to be determined by economic conditions and regulatory environments within individual countries to follow larger financial market trends. The Black-Litterman model combined with the minimum variance strategy enables investors to manage risks effectively in their cryptocurrency investments.

The G7 countries exhibit different levels of risk and return between green and non-green cryptocurrency portfolios which demonstrates that non-green portfolios deliver higher returns yet present substantial volatility. Green portfolios provide long-term investors an appealing investment strategy because they deliver consistent returns. Portfolio allocation strategies that achieve top performance in each nation match the financial rules alongside investor practices of their respective countries.

Conclusion

This research examines how conventional assets can work together with green, energy and non-green cryptocurrencies in portfolio optimization specifically for G7 nations. The research analyzes cryptocurrency portfolio optimization strategies through G7 nations using machine learning models to develop and assess portfolios subject to multiple constraints. The initial model determined optimal portfolio divisions through a train-test split of 80%-20% and then retraied on the complete dataset for refinement. Performance outcomes from green and non-green portfolios demonstrate different results across nations because of specific financial conditions together with government regulations and investor behaviors in each nation.

Different portfolio strategies demonstrate compatibility with individual market characteristics of each country. In U.S. and Japan, the maximum sharpe portfolio showed best performance due to the financial markets possess strong structures and their institutions actively participate in investments. The investment cultures in Canada and Italy led to their selection of minimum variance portfolios. The Black-Litterman model established success in the UK by merging market expectations with real risk-return dynamics yet Germany chose maximum return portfolios because of its high risk tolerance. The French financial sector placed priority on risk-adjusted returns thus the optimized Sortino ratio strategy became the best fit.

Data shows that green portfolios produced lower risk levels and superior risk-return relation results compared to regular portfolios when sustainability policies are defined specifically in the respective countries. Although non-green portfolios delivered increased returns they functioned as speculative investments that faced high market volatility. Portfolio managers should include regulatory standards together with economic conditions to make better investment decisions.

The usage of machine learning techniques performed a vital function in optimizing portfolio building procedures which resulted in improved market adjustment capabilities. The portfolio constraints underwent robustness checks through Excel-based testing to confirm their reliability in the optimization process. Results of predicted performance compared to actual results confirmed that machine learning successfully optimized asset allocation through its application.The research shows that investors need to build portfolios based on market conditions that exist in their target countries. Long-term stable investors can choose green portfolios which offer reliability while risk-seeking investors may select non-green portfolio strategies. Research in this field should concentrate on dynamic portfolio rebalancing methods which implement decentralized finance (DeFi) technology to optimize investment portfolios.

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Appendix A

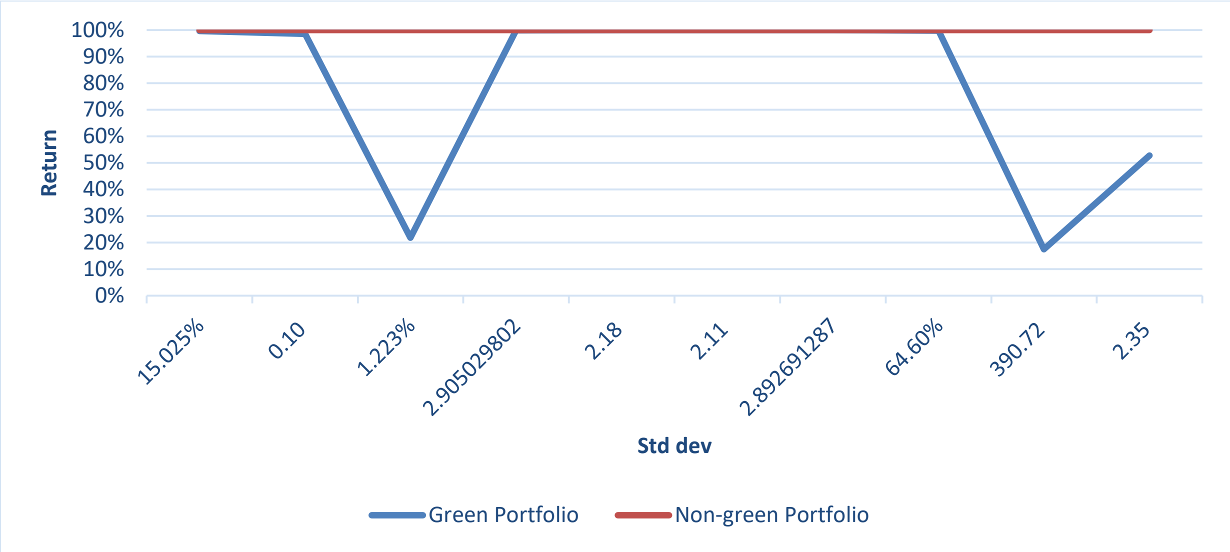
Abbreviation

Sp	Sharpe ratio
Mvp	Minimum Variance portfolio
Sd	Standard deviation
mRp	Return portfolio
Var	Variance
MPT	Modern Portfolio Theory
Non-Green Cryptocurrency Portfolio	NGCP
Green Cryptocurrency Portfolio	GCP

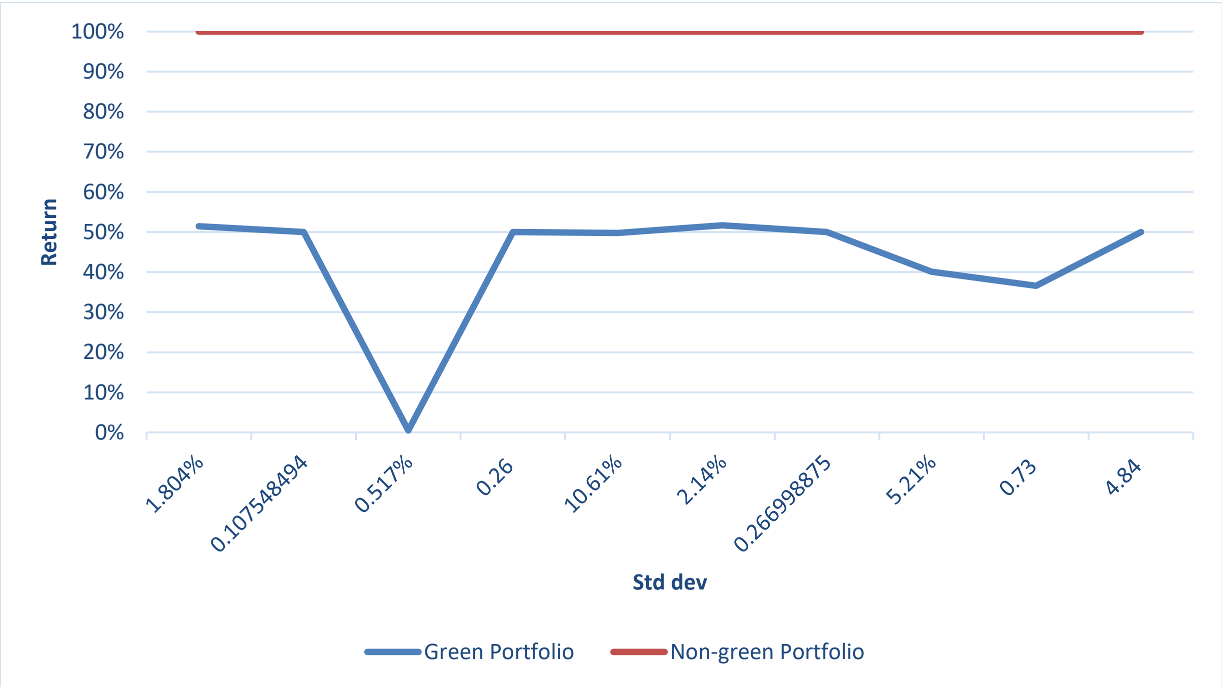
Appendix B

Comparison between green and Non-green portfolios

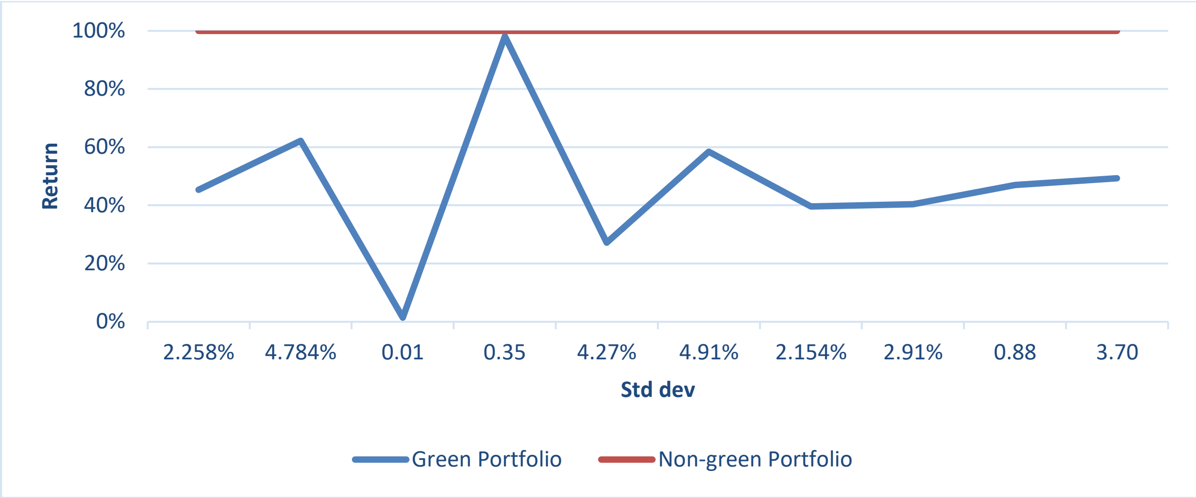
1): USA



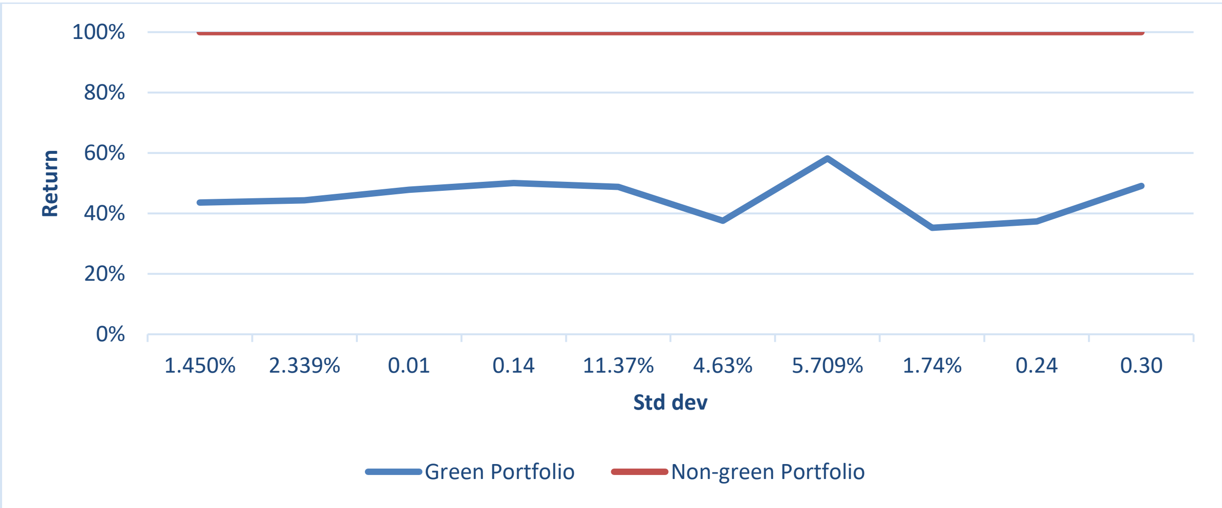
2): UK



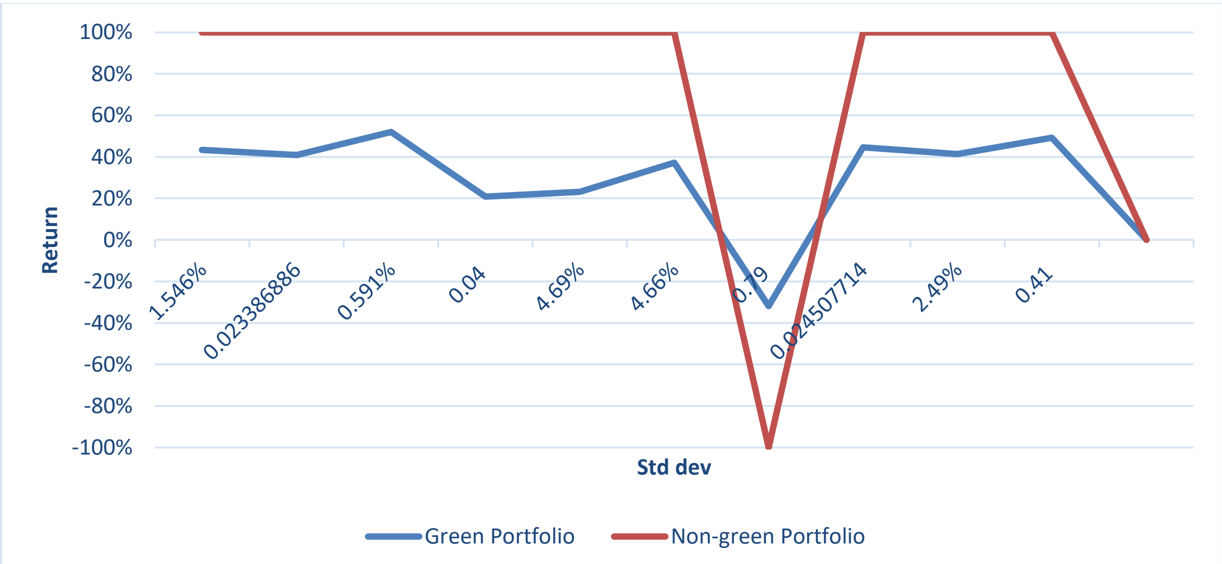
3): Canada



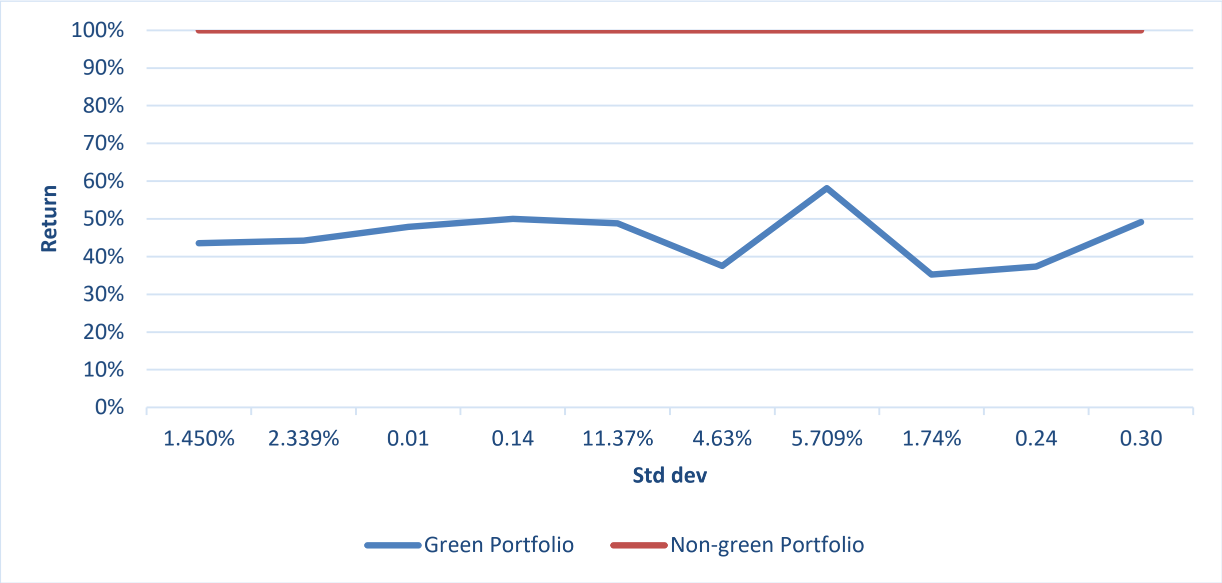
4): France



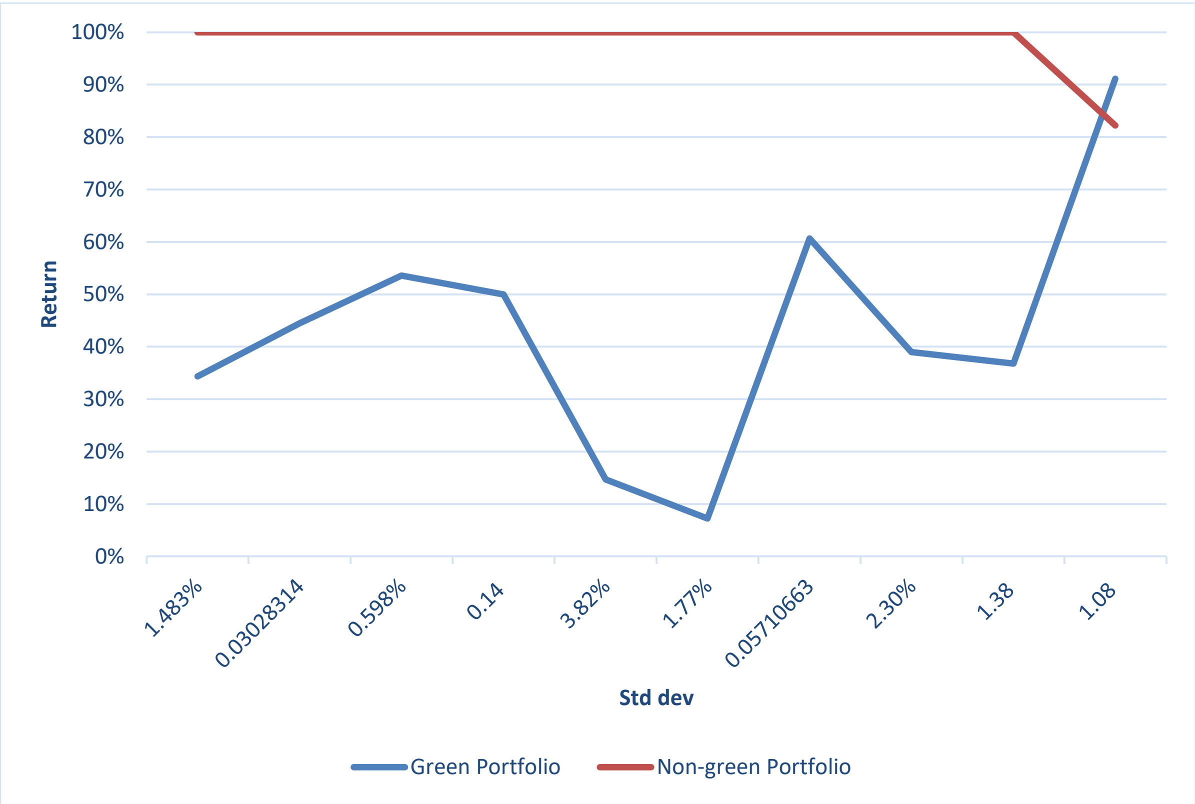
5): Germany



6): Italy



7): Japan



Appendix C : Machine learning training & testing

1): USA green

```
Portfolio Metrics Comparison (Training Data vs Testing Data):
               Metric  Training Data  Testing Data
0              Return      17.341722      0.176529
1            Variance     298.232120      0.165938
2  Standard Deviation      17.269398      0.407355
3        Sharpe Ratio       1.003609      0.408805

Actual vs Predicted Portfolio Performance (Testing Period):
                        Date  Actual Portfolio Performance  \
0  2024-04-28 00:00:00+00:00                     -0.022548
1  2024-04-29 00:00:00+00:00                     -0.038803
2  2024-04-30 00:00:00+00:00                     -0.079431
3  2024-05-01 00:00:00+00:00                     -0.100528
4  2024-05-02 00:00:00+00:00                     -0.085757
..                       ...                           ...
58 2024-06-25 00:00:00+00:00                      0.036341
59 2024-06-26 00:00:00+00:00                      0.013858
60 2024-06-27 00:00:00+00:00                      0.041754
61 2024-06-28 00:00:00+00:00                      0.014510
62 2024-06-29 00:00:00+00:00                      0.023966

    Predicted Portfolio Performance
0                         -0.022548
1                         -0.038803
2                         -0.079431
3                         -0.100528
4                         -0.085757
..                              ...
58                         0.036341
59                         0.013858
60                         0.041754
61                         0.014510
62                         0.023966

[63 rows x 3 columns]
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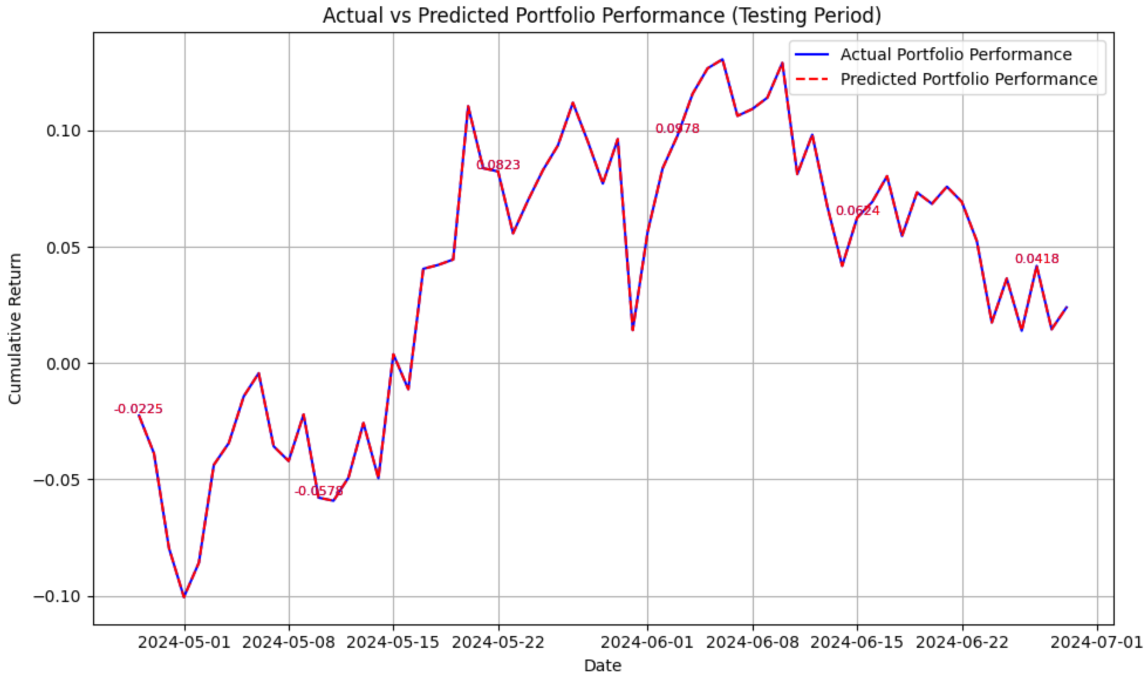


2): USA Non-green portfolio

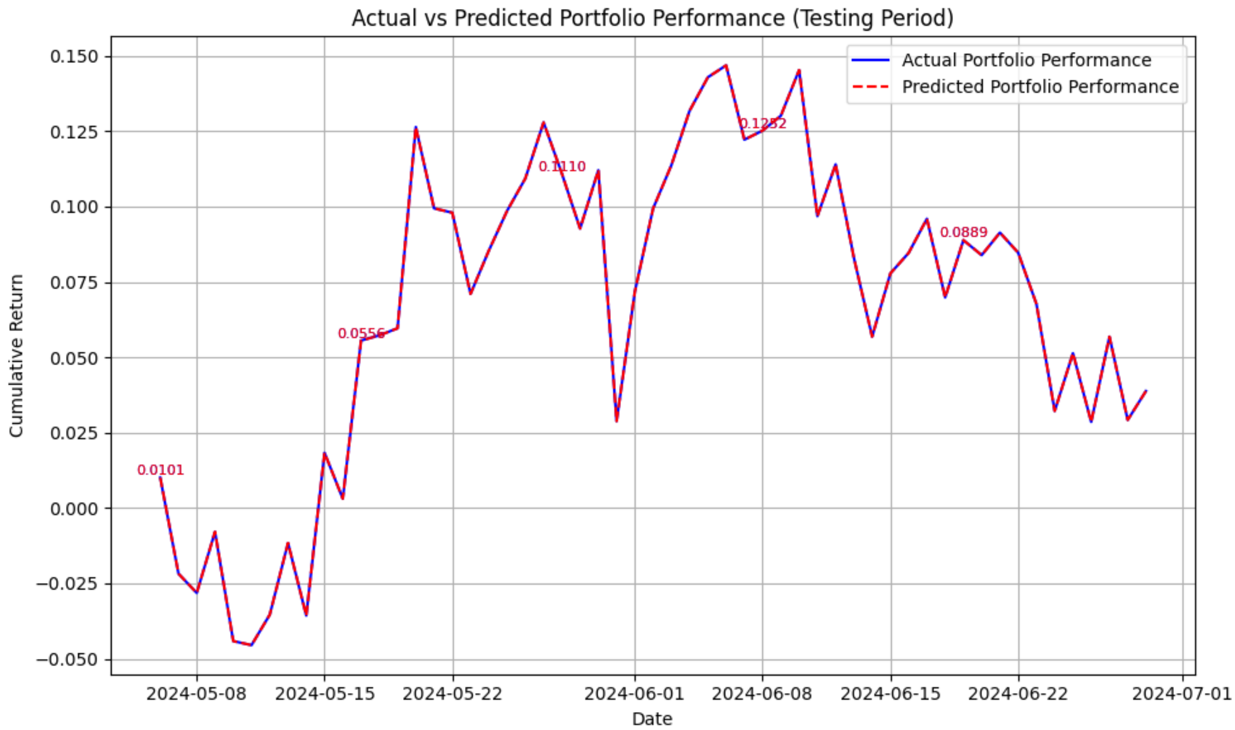
Portfolio Metrics Comparison (Training Data vs Testing Data):

	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



3): UK green portfolio

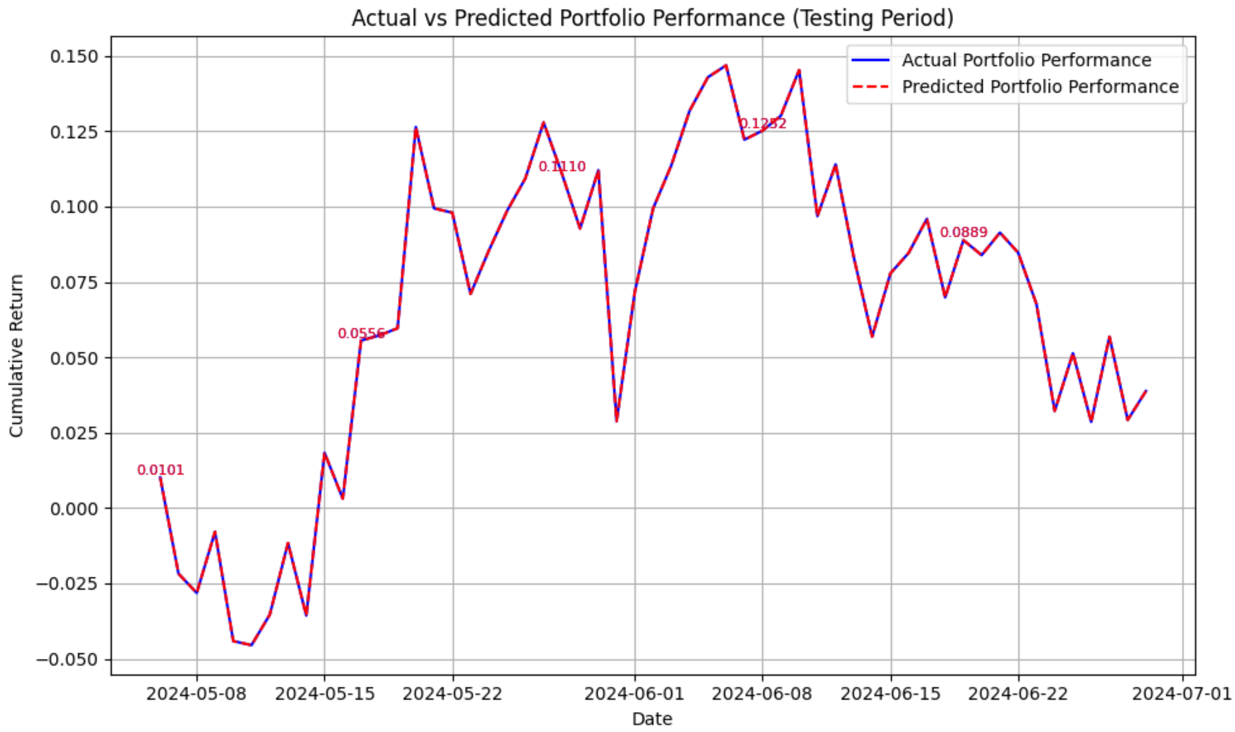
Portfolio Metrics Comparison (Training Data vs Testing Data):

	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



4): UK Non-green Portfolio

```
Portfolio Metrics Comparison (Training Data vs Testing Data):
               Metric  Training Data  Testing Data
0              Return       1.691174      0.323449
1            Variance       4.631343      0.882734
2  Standard Deviation       2.152055      0.939539
3        Sharpe Ratio       0.781195      0.333620

Actual vs Predicted Portfolio Performance (Testing Period):
                         Date  Actual Portfolio Performance  \
0   2023-08-02 00:00:00+00:00                     -0.026786
1   2023-08-03 00:00:00+00:00                     -0.026786
2   2023-08-04 00:00:00+00:00                     -0.033482
3   2023-08-05 00:00:00+00:00                     -0.035714
4   2023-08-06 00:00:00+00:00                     -0.046875
..                        ...                           ...
328 2024-06-25 00:00:00+00:00                     -0.147321
329 2024-06-26 00:00:00+00:00                     -0.151786
330 2024-06-27 00:00:00+00:00                     -0.156250
331 2024-06-28 00:00:00+00:00                     -0.174107
332 2024-06-29 00:00:00+00:00                     -0.127232

     Predicted Portfolio Performance
0                          -0.026786
1                          -0.026786
2                          -0.033482
3                          -0.035714
4                          -0.046875
..                               ...
328                        -0.147321
329                        -0.151786
330                        -0.156250
331                        -0.174107
332                        -0.127232

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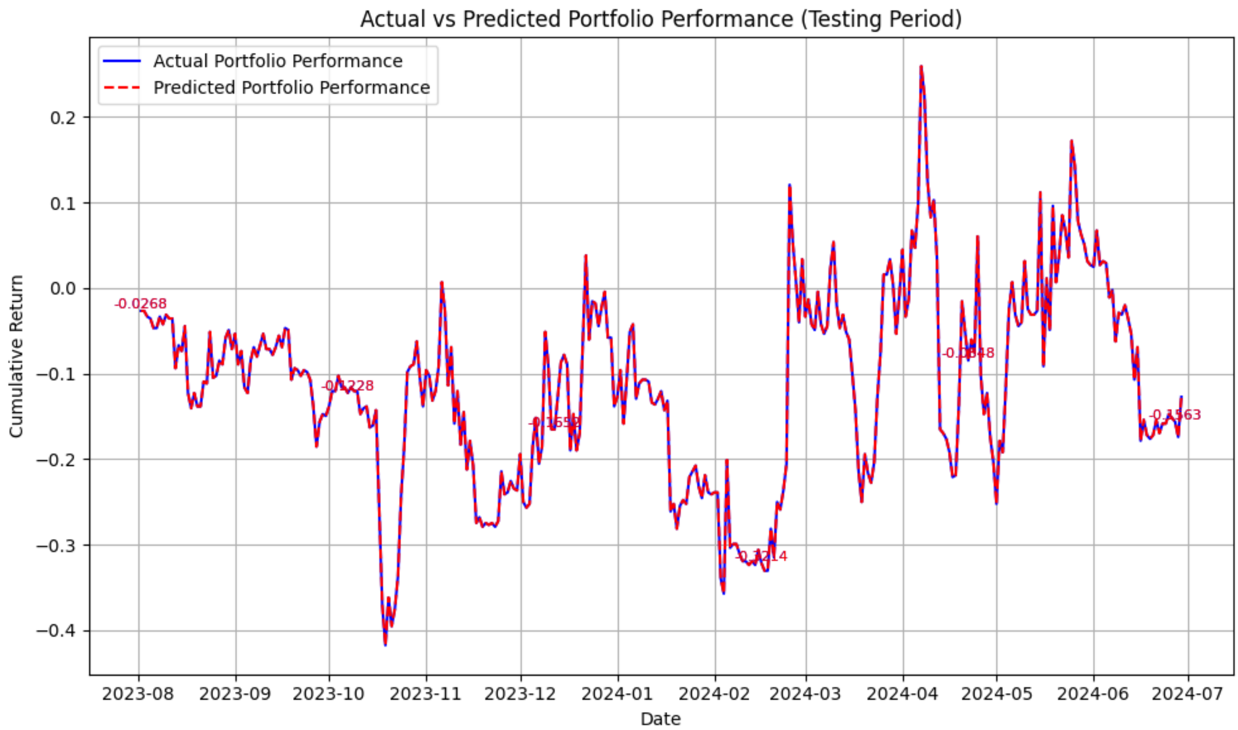
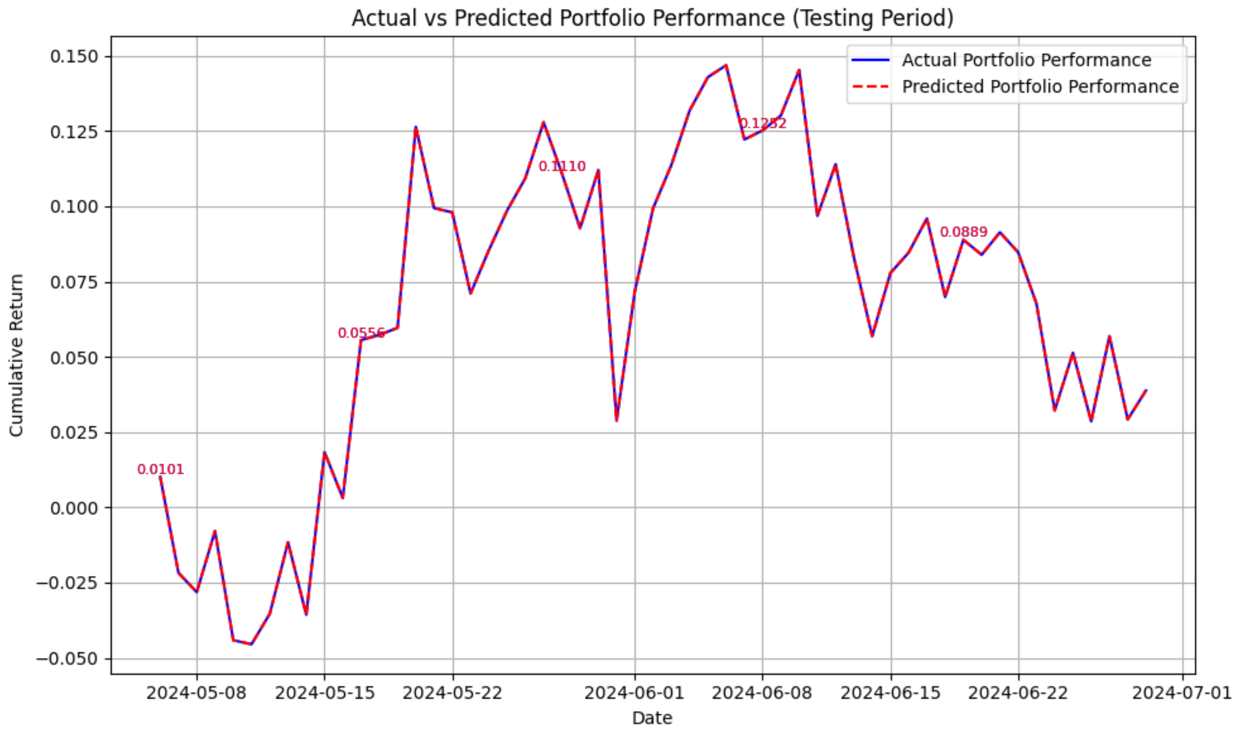


5): Canada Green Portfolio

```
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
```



6): Canada Non-green Portfolio

```
Portfolio Metrics Comparison (Training Data vs Testing Data):
              Metric  Training Data  Testing Data
0             Return       1.562227      0.297910
1           Variance       4.540010      0.845534
2 Standard Deviation       2.130730      0.919529
3       Sharpe Ratio       0.728496      0.313106

Actual vs Predicted Portfolio Performance (Testing Period):
                         Date  Actual Portfolio Performance  \
0   2023-07-16 00:00:00+00:00                      0.030702
1   2023-07-17 00:00:00+00:00                      0.024123
2   2023-07-18 00:00:00+00:00                      0.028509
3   2023-07-19 00:00:00+00:00                      0.026316
4   2023-07-20 00:00:00+00:00                      0.024123
..                        ...                           ...
345 2024-06-25 00:00:00+00:00                     -0.162281
346 2024-06-26 00:00:00+00:00                     -0.166667
347 2024-06-27 00:00:00+00:00                     -0.171053
348 2024-06-28 00:00:00+00:00                     -0.188597
349 2024-06-29 00:00:00+00:00                     -0.142544

     Predicted Portfolio Performance
0                           0.030702
1                           0.024123
2                           0.028509
3                           0.026316
4                           0.024123
..                               ...
345                        -0.162281
346                        -0.166667
347                        -0.171053
348                        -0.188597
349                        -0.142544

[350 rows x 3 columns]
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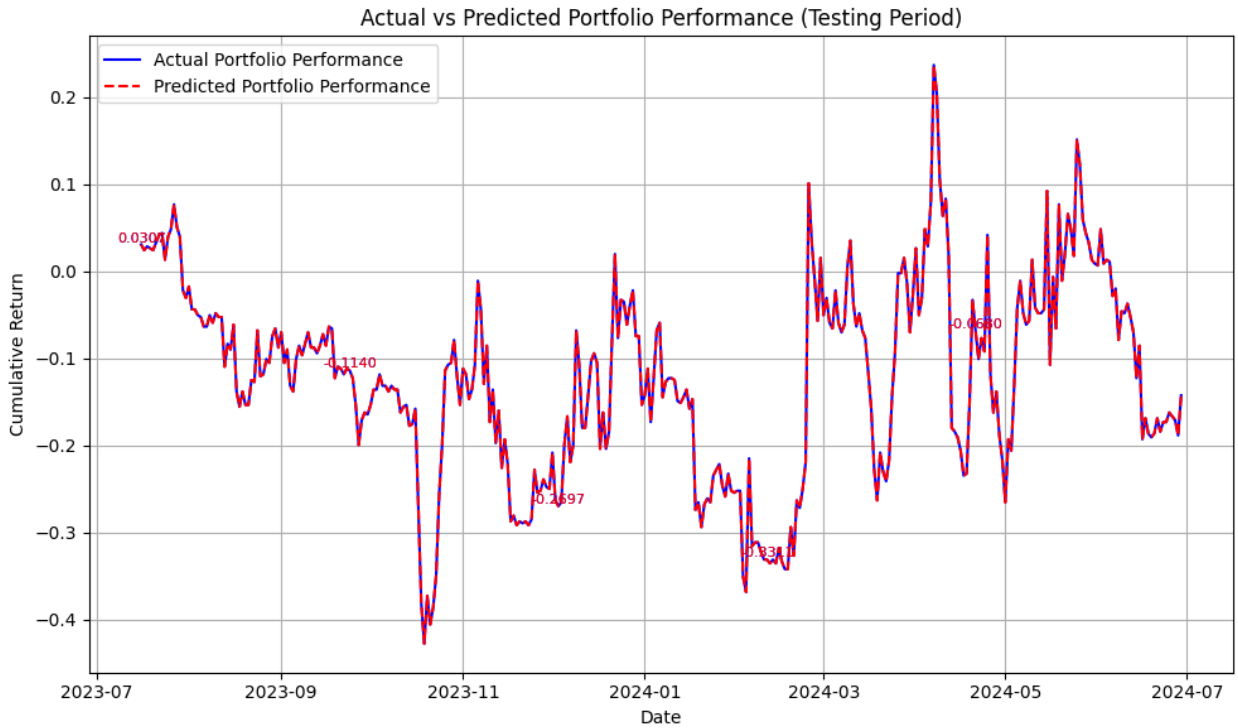
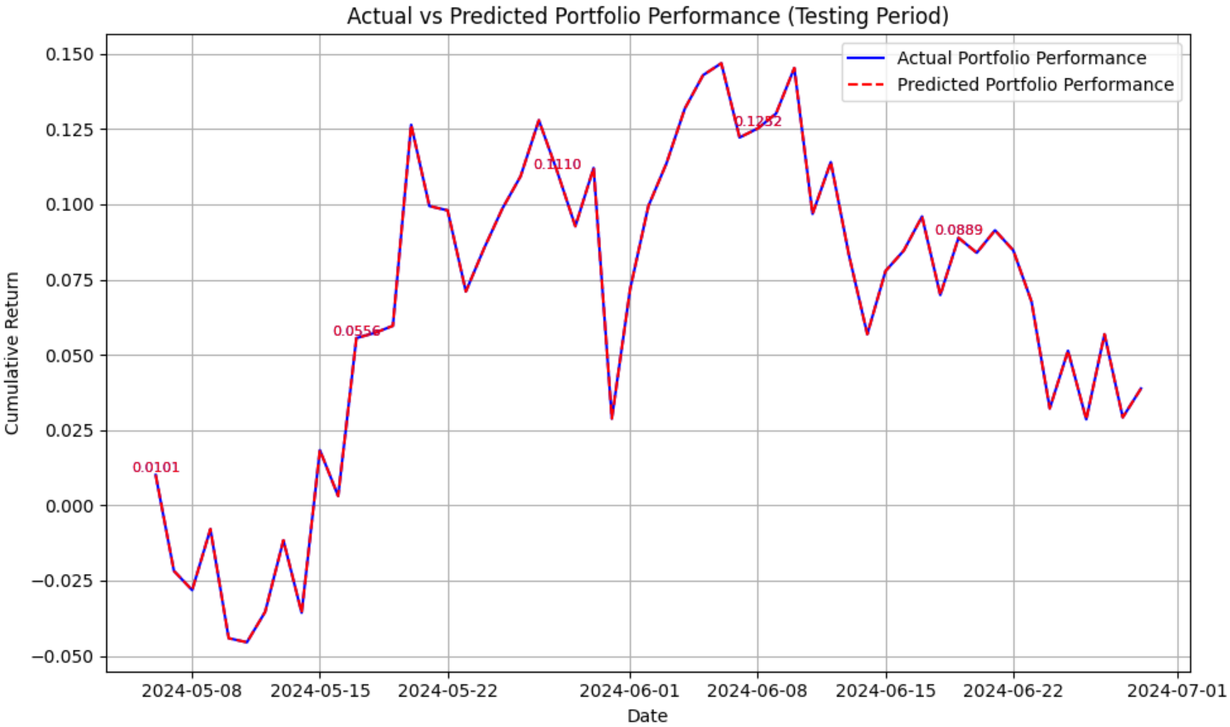


7): Germany green portfolio

```
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
```



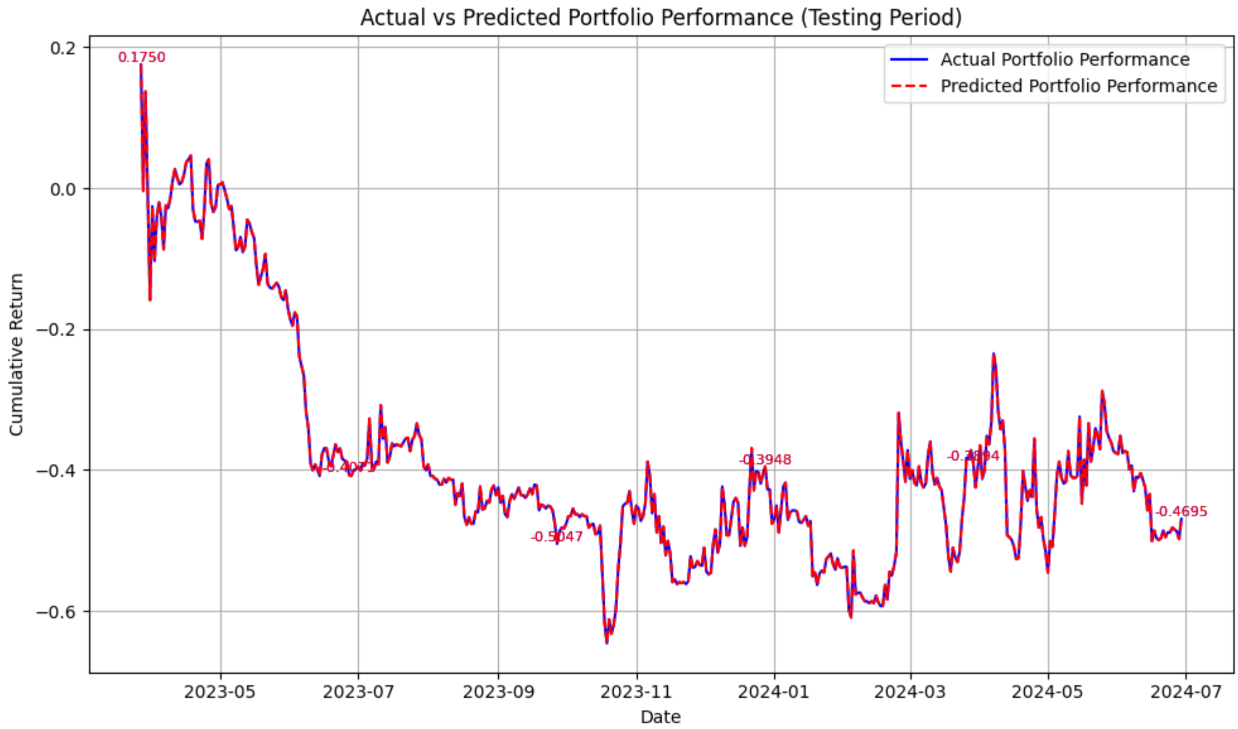
8): Germany Non-green portfolio

```
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

[461 rows x 3 columns]
```

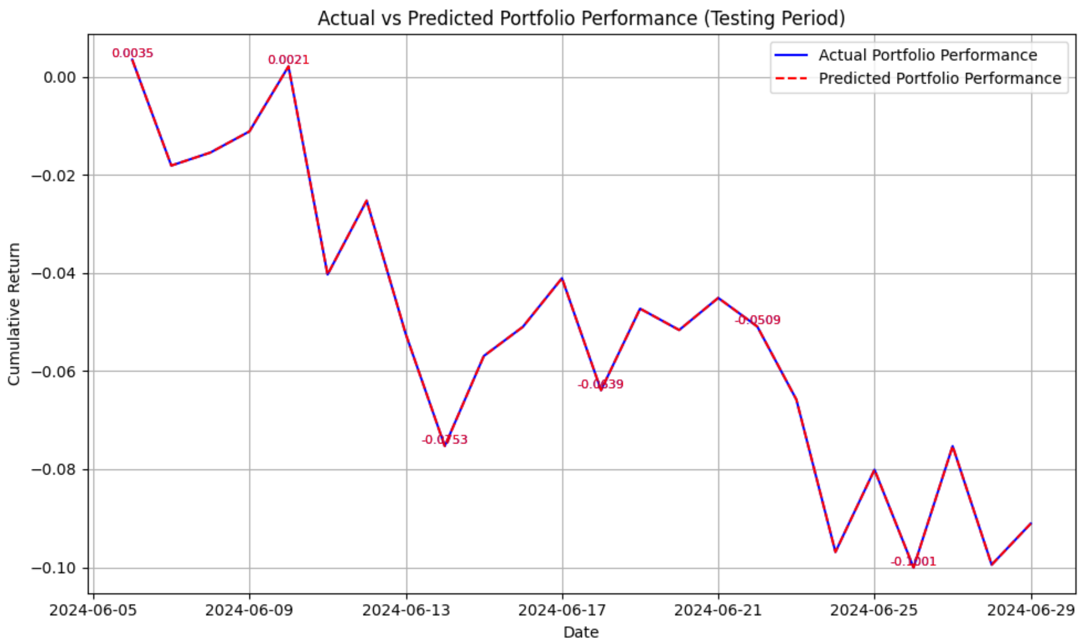


9): France green portfolio

```
Portfolio Metrics Comparison (Training Data vs Testing Data):
               Metric  Training Data  Testing Data
0              Return      44.770144     -0.953377
1            Variance     798.264102      0.098194
2  Standard Deviation      28.253568      0.313359
3        Sharpe Ratio       1.584230     -3.074350

Actual vs Predicted Portfolio Performance (Testing Period):
                        Date  Actual Portfolio Performance  \
0  2024-06-06 00:00:00+00:00                      0.003459
1  2024-06-07 00:00:00+00:00                     -0.018119
2  2024-06-08 00:00:00+00:00                     -0.015470
3  2024-06-09 00:00:00+00:00                     -0.011158
4  2024-06-10 00:00:00+00:00                      0.002098
5  2024-06-11 00:00:00+00:00                     -0.040333
6  2024-06-12 00:00:00+00:00                     -0.025268
7  2024-06-13 00:00:00+00:00                     -0.052417
8  2024-06-14 00:00:00+00:00                     -0.075297
9  2024-06-15 00:00:00+00:00                     -0.056932
10 2024-06-16 00:00:00+00:00                     -0.050984

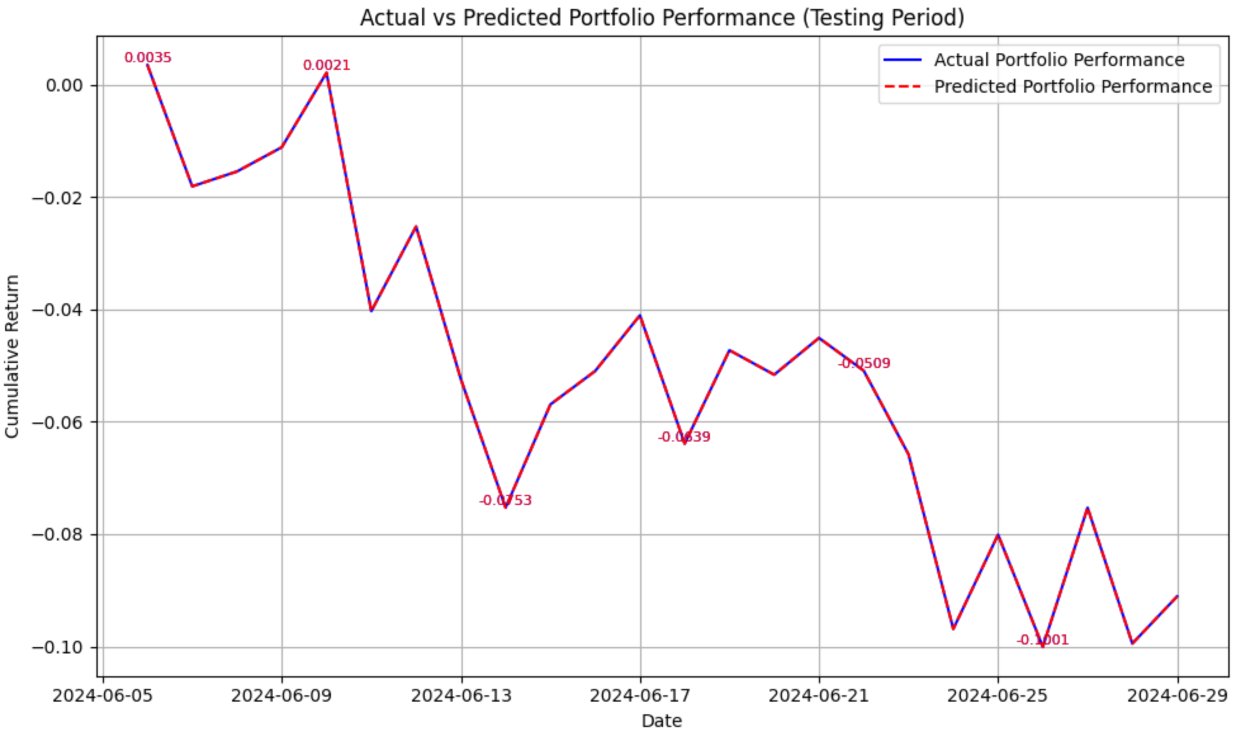
    Predicted Portfolio Performance
0                          0.003459
1                         -0.018119
2                         -0.015470
3                         -0.011158
4                          0.002098
5                         -0.040333
6                         -0.025268
7                         -0.052417
8                         -0.075297
9                         -0.056932
10                        -0.050984
```



10): France Non-green portfolio

```
Portfolio Metrics Comparison (Training Data vs Testing Data):
               Metric  Training Data  Testing Data
0              Return      44.770144     -0.953377
1            Variance     798.264102      0.098194
2  Standard Deviation      28.253568      0.313359
3        Sharpe Ratio       1.584230     -3.074350

Actual vs Predicted Portfolio Performance (Testing Period):
                        Date  Actual Portfolio Performance  \
0  2024-06-06 00:00:00+00:00                      0.003459
1  2024-06-07 00:00:00+00:00                     -0.018119
2  2024-06-08 00:00:00+00:00                     -0.015470
3  2024-06-09 00:00:00+00:00                     -0.011158
4  2024-06-10 00:00:00+00:00                      0.002098
5  2024-06-11 00:00:00+00:00                     -0.040333
6  2024-06-12 00:00:00+00:00                     -0.025268
7  2024-06-13 00:00:00+00:00                     -0.052417
8  2024-06-14 00:00:00+00:00                     -0.075297
9  2024-06-15 00:00:00+00:00                     -0.056932
10 2024-06-16 00:00:00+00:00                     -0.050984
    Predicted Portfolio Performance
0                          0.003459
1                         -0.018119
2                         -0.015470
3                         -0.011158
4                          0.002098
5                         -0.040333
6                         -0.025268
7                         -0.052417
8                         -0.075297
9                         -0.056932
10                        -0.050984
```

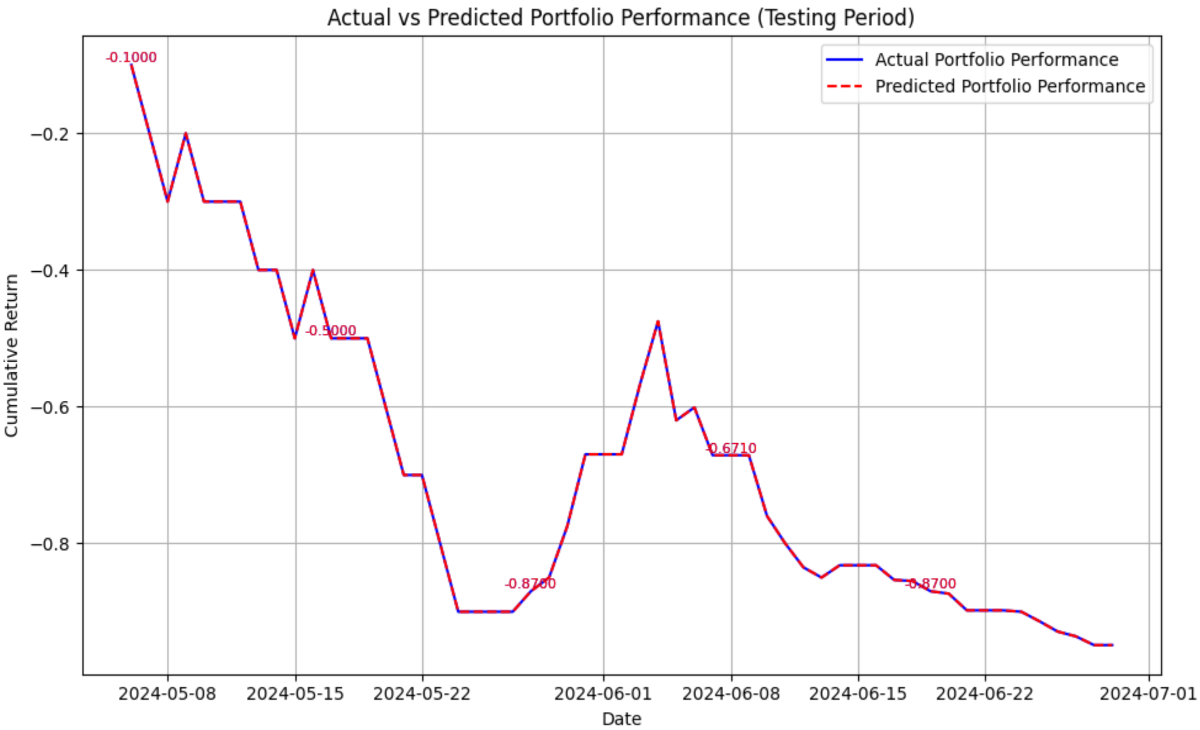


11): Italy green portfolio

```
Portfolio Metrics Comparison (Training Data vs Testing Data):
               Metric  Training Data  Testing Data
0              Return      47.520300     -9.220239
1            Variance    2786.308186      8.088003
2  Standard Deviation      52.785492      2.843941
3        Sharpe Ratio       0.900064     -3.245580

Actual vs Predicted Portfolio Performance (Testing Period):
                        Date  Actual Portfolio Performance  \
0  2024-05-06 00:00:00+00:00                       -0.1000
1  2024-05-07 00:00:00+00:00                       -0.2000
2  2024-05-08 00:00:00+00:00                       -0.3000
3  2024-05-09 00:00:00+00:00                       -0.2000
4  2024-05-10 00:00:00+00:00                       -0.3000
5  2024-05-11 00:00:00+00:00                       -0.3000
6  2024-05-12 00:00:00+00:00                       -0.3000
7  2024-05-13 00:00:00+00:00                       -0.4000
8  2024-05-14 00:00:00+00:00                       -0.4000
9  2024-05-15 00:00:00+00:00                       -0.5000
10 2024-05-16 00:00:00+00:00                       -0.4000

    Predicted Portfolio Performance
0                           -0.1000
1                           -0.2000
2                           -0.3000
3                           -0.2000
4                           -0.3000
5                           -0.3000
6                           -0.3000
7                           -0.4000
8                           -0.4000
9                           -0.5000
10                          -0.4000
```

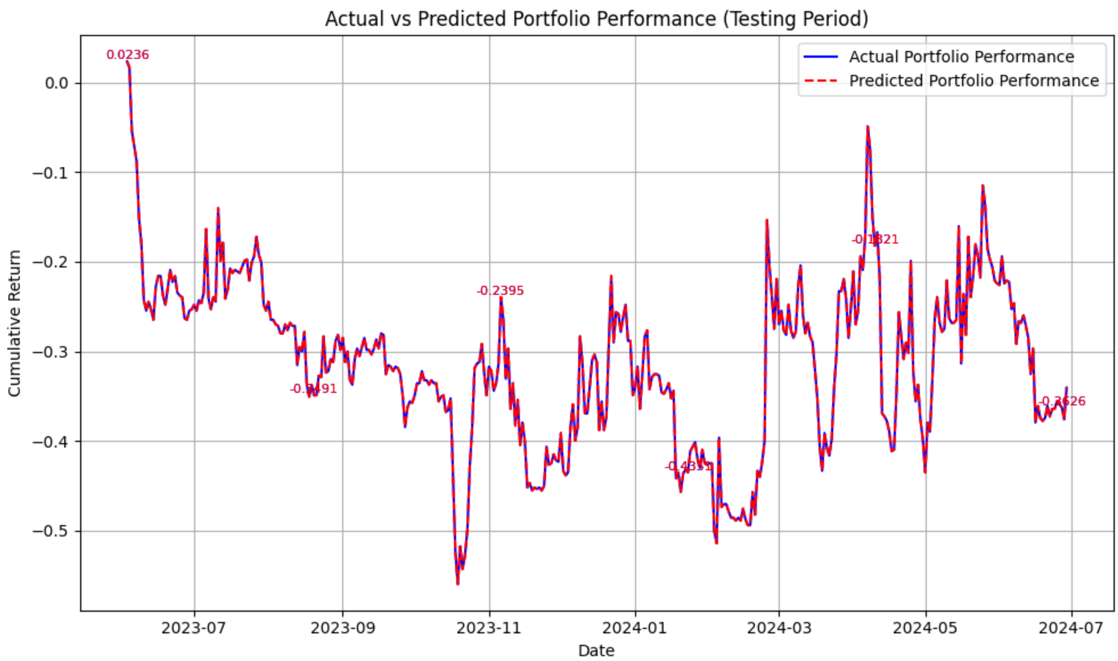


12): Italy Non-green portfolio

```
Portfolio Metrics Comparison (Training Data vs Testing Data):
               Metric  Training Data  Testing Data
0              Return       1.368886      0.120765
1            Variance       4.199207      0.801118
2  Standard Deviation       2.049197      0.895052
3        Sharpe Ratio       0.663131      0.123753

Actual vs Predicted Portfolio Performance (Testing Period):
                         Date  Actual Portfolio Performance  \
0   2023-06-03 00:00:00+00:00                      0.023609
1   2023-06-04 00:00:00+00:00                      0.016863
2   2023-06-05 00:00:00+00:00                     -0.053963
3   2023-06-06 00:00:00+00:00                     -0.070826
4   2023-06-07 00:00:00+00:00                     -0.087690
..                        ...                           ...
388 2024-06-25 00:00:00+00:00                     -0.355818
389 2024-06-26 00:00:00+00:00                     -0.359191
390 2024-06-27 00:00:00+00:00                     -0.362563
391 2024-06-28 00:00:00+00:00                     -0.376054
392 2024-06-29 00:00:00+00:00                     -0.340641

     Predicted Portfolio Performance
0                           0.023609
1                           0.016863
2                          -0.053963
3                          -0.070826
4                          -0.087690
..                               ...
388                        -0.355818
389                        -0.359191
390                        -0.362563
391                        -0.376054
392                        -0.340641
```

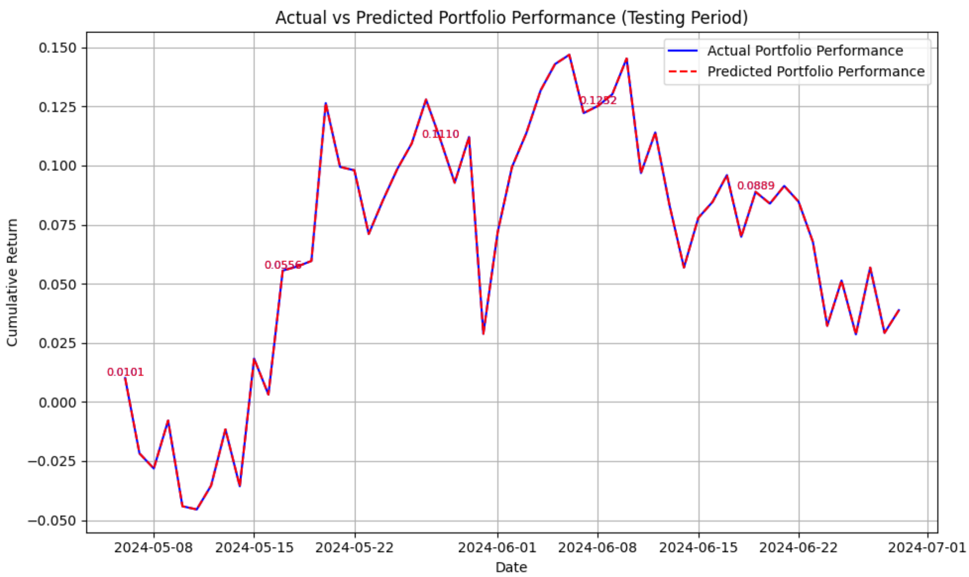


13): Japan green portfolio

```
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
```



14): Japan non-green portfolio

```
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

[461 rows x 3 columns]
```