Policy Research Journal
ISSN (E): 3006-7030 ISSN (P) : 3006-7022 Volume 4, Issue 4, 2026

LSTM-BASED PREDICTIVE MODELLING FOR GREEN AND NON-GREEN CRYPTOCURRENCY PORTFOLIO OPTIMISATION: A CROSS-COUNTRY ANALYSIS

Sumiya Tahir[1], Syeda Fizza Abbas[2], Wajid Alim[*3]

[1]*Lecturer, Department of Accounting & Finance, Kinnaird College for Women University, Lahore*
[2]*Assistant Professor & Head of Department Accounting & Finance, Kinnaird College for Women University, Lahore*
[*3]*Assistant Professor, Lahore School of Accountancy & Finance, University of Lahore*

[1]sumiya.tahir@kinnaird.edu.pk, [2]fizza.abbas@kinnaird.edu.pk, [*3]wajid@uolcc.edu.pk

DOI: https://doi.org/10.5281/zenodo.19915886

Keywords
LSTM; Deep Learning; Cryptocurrency; Green Finance; Portfolio Optimisation; ESG Investing; Financial Forecasting; Time Series; Recurrent Neural Networks; Sustainable Investing

Article History
Received: 11 February 2026
Accepted: 21 March 2026
Published: 30 April 2026

Corresponding Author: *
Wajid Alim

Abstract
This study applies Long Short-Term Memory (LSTM) neural networks to forecast asset prices within green and non-green cryptocurrency portfolios across ten geographically diverse markets: the United States, the United Kingdom, Canada, Germany, France, Italy, Japan, India, Russia, Brazil, South Africa, and China. The LSTM architecture is selected for its demonstrated capacity to capture long-range temporal dependencies within financial time series data, overcoming the vanishing gradient limitations of conventional recurrent networks. Employing daily closing price data for the period ending June 2024, the research constructs and evaluates portfolios that blend cryptocurrencies with equities, commodities, and sector-specific instruments within each national context. Results indicate that LSTM models achieve moderate accuracy for stable conventional equities and select commodities, while systematically overestimating or underestimating highly volatile cryptocurrency assets. Notable cross-regional heterogeneity is observed, with BRICS economies displaying wider prediction divergences compared to G7 counterparts.

INTRODUCTION

The rapid evolution of financial markets over the past decade has been significantly shaped by two parallel developments: the proliferation of cryptocurrencies and the growing integration of environmental, social, and governance (ESG) principles into investment decision-making. These forces have collectively transformed the landscape of portfolio construction, introducing new layers of complexity that extend beyond traditional asset allocation frameworks(Henriksson, Livnat, Pfeifer, & Stumpp, 2019). Investors today are increasingly required to navigate markets characterized by extreme volatility, rapidly shifting correlations across asset classes, and emerging sustainability constraints that influence both risk and return dynamics. In this context, conventional econometric and statistical forecasting models often fall short in capturing the nonlinear and high-dimensional relationships inherent in modern financial time series data(Cesarone, Martino, & Carleo, 2022). Cryptocurrencies, in particular, represent one of the most challenging asset classes for predictive modeling(Luo, Feng, Xu, Tasca, & Liu, 2025). Unlike traditional equities or commodities, digital assets exhibit highly irregular price movements, frequent regime shifts, and sensitivity to external shocks such as regulatory announcements, technological updates, and macroeconomic sentiment changes. These characteristics render linear models such as autoregressive integrated moving average (ARIMA) or simple regression frameworks less effective in generating reliable forecasts. Consequently, there has been a growing interest in machine learning and deep learning approaches capable of learning complex temporal dependencies directly from raw financial data(Shamshad, Ullah, Ullah, Kebande, Ullah, & Al-Dhaqm, 2023).

Among deep learning architectures, Long Short-Term Memory (LSTM) networks have emerged as one of the most effective tools for time series forecasting in financial applications. First introduced by Hochreiter and Schmidhuber (1997), LSTM networks address the limitations of traditional recurrent neural networks (RNNs), particularly the vanishing and exploding gradient problems that hinder the learning of long-term dependencies. By incorporating specialized gating mechanisms—including input, forget, and output gates—LSTM models are able to selectively retain or discard information over extended time horizons. This makes them particularly well-suited for financial forecasting tasks, where historical price patterns, cyclical trends, and macroeconomic influences must be simultaneously considered to generate meaningful predictions(Kumar, 2019; Livieris, Pintelas, Stavroyiannis, & Pintelas, 2020).

The application of LSTM networks to financial forecasting has been widely explored in the literature. Empirical studies such as (Cao, Li, & Li, 2019)demonstrate that LSTM-based models outperform traditional machine learning techniques, including random forests and logistic regression, in predicting stock market movements, particularly within major indices such as the S&P 500. (Wang, Hong, Dong, Li, & Hu, 2024) provide evidence that LSTM models achieve lower forecasting errors compared to classical statistical approaches such as ARIMA across various financial instruments. In the context of cryptocurrencies.There are various studies that highlight the superiority of LSTM architectures over Bayesian-optimized ARIMA models in predicting Bitcoin price trajectories, further reinforcing the suitability of deep learning methods for highly volatile digital asset markets. Despite these advancements, a key limitation in existing research is the narrow focus on either conventional financial assets or a single cryptocurrency, most commonly Bitcoin or Ethereum. Relatively few studies extend LSTM-based forecasting frameworks to diversified portfolios that incorporate both traditional assets and digital currencies simultaneously. Even fewer investigations consider the integration of environmental sustainability criteria into cryptocurrency portfolio design. This gap is particularly important given the increasing emphasis on ESG investing, which has begun to influence asset selection across global financial markets(Banerjee, 2025; Nagesh, Jayudu, Rao, Hariprasad, Naresh, & Balaji, 2025).

In response to these limitations, the present study introduces a comprehensive LSTM-based predictive modelling framework applied to both green and non-green cryptocurrency portfolios across multiple national markets. Green cryptocurrencies—such as Powerledger (POWR), WePower (WPR), Electrify.Asia (ELEC), and SunContract (SNC)—are designed with lower environmental impact in mind, often utilizing proof-of-stake or energy-efficient consensus mechanisms. These assets are increasingly viewed as complementary to ESG-aligned equity and commodity investments, as they offer exposure to blockchain-based innovations that support renewable energy systems and sustainable infrastructure development(Ali, Khurram, Sensoy, & Vo, 2024).By contrast, non-green cryptocurrency portfolios typically include widely traded digital assets such as Bitcoin and Ethereum, which, despite their dominance and liquidity, have been criticized for their relatively high energy consumption and environmental footprint. The comparative analysis of these two portfolio categories allows for a nuanced understanding of whether sustainability-aligned digital assets exhibit different predictive characteristics under deep learning models, and whether they respond differently to global financial conditions(Niu & Gao, 2026).

A distinguishing feature of this study is its cross-country analytical framework, which evaluates LSTM forecasting performance across a diverse set of ten geographically and economically distinct markets, including the United States, United Kingdom, Canada, Germany, France, Italy, Japan, India, Russia, Brazil, South Africa, and China. These countries represent a mixture of developed G7 economies and emerging BRICS and developing markets, each characterized by unique regulatory environments, macroeconomic conditions, and levels of cryptocurrency adoption. This heterogeneity provides an ideal setting for examining whether LSTM models demonstrate consistent predictive accuracy across different financial ecosystems or whether their performance is significantly influenced by country-specific factors(Gadi & Sicilia, 2022).

Cross-country portfolio modeling introduces additional layers of complexity, including currency fluctuations, varying levels of market efficiency, and differential exposure to global economic shocks. Prior research by suggests that localized deep learning models often outperform globally pooled datasets in financial forecasting tasks, as they are better able to capture region-specific market dynamics. Building on this insight, the current study develops country-specific LSTM models to ensure that local market characteristics are adequately represented in the predictive process(Gökgöz, Afjal, Bejaoui, & Jeribi, 2024). The primary objective of this research is to evaluate the effectiveness of LSTM networks in forecasting asset prices within diversified portfolios that integrate cryptocurrencies, equities, commodities, and sector-specific financial instruments. By constructing and analyzing portfolios within each national context, the study aims to assess not only the predictive accuracy of LSTM models but also their robustness across different asset classes and geographic regions. Particular attention is given to the comparative performance between green and non-green cryptocurrency portfolios, as well as the extent to which model accuracy varies between stable conventional assets and highly volatile digital currencies(Wu & Chitpattanapaibul, 2025).

Preliminary evidence suggests that LSTM models tend to achieve moderate predictive accuracy when applied to stable assets such as established equities and commodities, where price movements are relatively structured and influenced by identifiable macroeconomic factors. However, the models exhibit systematic overestimation and underestimation when applied to highly volatile cryptocurrency assets, reflecting the inherent unpredictability and noise-driven nature of digital asset markets. Furthermore, notable cross-regional heterogeneity is observed, with emerging economies—particularly those within the BRICS group—demonstrating wider deviations in predictive performance compared to more stable G7 economies. This suggests that market maturity and regulatory stability may play a significant role in determining the effectiveness of deep learning forecasting approaches(Eleuch, Souissi, & Mroua, 2025). In summary, this study contributes to the growing body of literature on financial forecasting and deep learning by extending LSTM-based modeling to a multi-asset, multi-country portfolio framework that integrates sustainability considerations. By jointly analyzing green and non-green cryptocurrencies across diverse economic contexts, the research provides new insights into the limitations and strengths of LSTM networks in real-world financial applications. It also highlights the importance of geographic and asset-class heterogeneity in shaping predictive performance, thereby offering valuable implications for both academic research and practical portfolio management in an increasingly complex global financial system.

2. Literature Review

2.1 Deep Learning in Financial Time Series Forecasting

The application of machine learning and deep learning techniques to financial time series forecasting has grown substantially over the past decade, driven by the increasing availability of high-frequency market data and advances in computational capacity. Traditional econometric models such as autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroskedasticity (GARCH), and linear regression frameworks have long been used for financial prediction tasks. However, these models are often limited by their underlying assumptions of linearity, stationarity, and relatively simple error structures, which are frequently violated in real-world financial markets characterized by nonlinear dynamics, structural breaks, and regime shifts(Hirani & Michael, 2024). In response to these limitations, researchers have increasingly turned toward machine learning methods capable of capturing complex, nonlinear relationships within financial data. Early approaches included support vector machines, decision trees, and ensemble methods such as random forests and gradient boosting. While these techniques demonstrated improved performance over classical statistical models in certain contexts, they remained limited in their ability to explicitly model sequential dependencies inherent in time series data(Perrin & Roncalli, 2020). The emergence of deep learning architectures marked a significant advancement in this field, particularly recurrent neural networks (RNNs), which are designed to process sequential inputs by maintaining internal memory states. However, standard RNNs suffer from vanishing and exploding gradient problems, which hinder their ability to learn long-term dependencies in extended sequences. This limitation led to the development of Long Short-Term Memory (LSTM) networks, which introduced gating mechanisms that regulate the flow of information over time and allow for more stable and effective learning of temporal patterns(Sherstinsky, 2020).

2.2 LSTM Networks and Their Role in Financial Prediction

Long Short-Term Memory networks, first introduced by (Hochreiter & Schmidhuber, 1997)), have become one of the most widely adopted deep learning architectures for financial forecasting tasks. LSTMs address the limitations of traditional RNNs by incorporating memory cells and three primary gates: input, forget, and output gates. These mechanisms enable the model to retain relevant historical information while discarding irrelevant data, making it particularly suitable for datasets with long-range temporal dependencies such as financial markets. Empirical evidence supporting the effectiveness of LSTM networks in financial prediction is well established. (Fischer & Krauss, 2018; Fischer, Krauss, & Treichel, 2018)demonstrated that LSTM-based models outperform traditional machine learning classifiers such as logistic regression and random forests in predicting stock price movements within the S&P 500 index. Their findings suggest that deep learning models are capable of extracting meaningful patterns from complex financial datasets that are not easily captured by conventional methods. Similarly, (Fischer, Krauss, & Treichel, 2018)conducted a comparative study between LSTM networks and classical forecasting techniques such as ARIMA. Their results indicated that LSTM models consistently achieved lower prediction errors across multiple financial time series, reinforcing the superiority of deep learning approaches in handling nonlinear and non-stationary data. These findings collectively highlight the growing consensus that LSTM networks represent a robust and flexible tool for financial forecasting applications.

2.3 Cryptocurrency Price Prediction Using Deep Learning

The cryptocurrency market presents unique challenges for predictive modeling due to its high volatility, speculative nature, and sensitivity to external shocks such as regulatory interventions, technological developments, and macroeconomic uncertainty. Unlike traditional financial assets, cryptocurrencies operate in a relatively immature and less regulated environment, which leads to frequent price fluctuations and abrupt structural changes in market behavior. Several studies have explored the application of LSTM networks to cryptocurrency price prediction. (McNally, Roche, & Caton, 2018)demonstrated that LSTM models outperform Bayesian-optimized ARIMA models in forecasting Bitcoin price movements, particularly in capturing short-term trends. Their study provided early evidence that deep learning techniques are well-suited to the nonlinear and volatile nature of cryptocurrency markets. Further research by (Mahajan, Patel, Parmar, Joao, Shekokar, & Degadwala, 2020)confirmed that LSTM architectures achieve lower forecasting errors compared to conventional machine learning models when applied to Bitcoin and other major cryptocurrencies. However, these studies also highlight a persistent limitation: while LSTM models perform relatively well in trend detection, their accuracy decreases significantly during periods of extreme volatility or market turbulence. This suggests that while deep learning models are powerful, they are not immune to the inherent unpredictability of cryptocurrency markets.Despite these advancements, most existing studies focus primarily on a limited set of dominant cryptocurrencies such as Bitcoin and Ethereum. As a result, there remains a significant research gap in understanding how deep learning models perform across diversified cryptocurrency portfolios that include both high-cap and emerging digital assets(Fauzi, Paiman, & Othman, 2020).

2.4 Green Cryptocurrencies and ESG-Oriented Digital Assets

In parallel with advancements in financial technology, there has been a growing emphasis on sustainable investing and ESG-aligned financial strategies. Within the cryptocurrency space, this has led to the emergence of so-called "green cryptocurrencies," which are designed to minimize environmental impact through energy-efficient consensus mechanisms such as proof-of-stake.Green cryptocurrencies, including Powerledger (POWR), WePower (WPR), Electrify.Asia (ELEC), and SunContract (SNC), are often associated with renewable energy applications and blockchain-based sustainability solutions. These assets are increasingly viewed as complementary to broader ESG investment strategies, particularly in portfolios that integrate environmental sustainability criteria(Jellouli, 2025).

(Vyas, Lunawat, Satapathy, Das, Sahu, & Mohanty, 2026)argue that green cryptocurrencies represent an important evolution in digital finance, offering environmentally conscious investors exposure to blockchain innovation without the high energy costs associated with proof-of-work systems. Despite this growing interest, academic literature on green cryptocurrencies remains limited, particularly in the context of predictive modeling and portfolio optimization.Most existing research focuses on environmental assessments or conceptual discussions of sustainability, rather than empirical forecasting or quantitative portfolio analysis. Consequently, there is a clear need for studies that examine whether green cryptocurrencies exhibit distinct statistical or predictive characteristics compared to traditional cryptocurrencies, especially when analyzed using advanced machine learning techniques such as LSTM networks(Kakinuma, 2025).

2.5 Cross-Country Financial Modeling and Market Heterogeneity

Financial markets are inherently influenced by country-specific factors, including regulatory frameworks, macroeconomic conditions, investor behavior, and levels of market maturity. As a result, predictive models developed in one market often do not generalize effectively to other geographic contexts. This has led to increased interest in cross-country financial modeling, where researchers attempt to evaluate model performance across multiple national markets.(Husain, Yii, Fung, & Busulwa, 2025) demonstrate that deep learning models trained on localized datasets tend to outperform globally pooled models in equity return prediction, particularly in Asian markets. Their findings suggest that financial data exhibit strong regional characteristics, and that incorporating country-specific information can significantly improve forecasting accuracy.Building on this perspective, cross-country analysis becomes particularly important when dealing with heterogeneous asset classes such as cryptocurrencies and ESG-linked instruments. Developed economies such as those in the G7 typically exhibit higher market efficiency, stronger regulatory oversight, and more stable financial systems, whereas emerging markets, including BRICS economies, often experience higher volatility, lower liquidity, and greater susceptibility to external shocks(Gadi & Sicilia, 2022). These structural differences can significantly influence the performance of machine learning models, including LSTM networks. In particular, models may exhibit higher accuracy in stable, mature markets while struggling to generalize in more volatile or less efficient environments. Despite this, limited research has systematically evaluated LSTM performance across multiple countries in a unified portfolio framework that includes both traditional and digital assets(DiPietro & Hager, 2020).

2.6 Research Gap and Positioning of the Present Study

The existing literature provides strong evidence for the effectiveness of LSTM networks in financial forecasting, particularly in stock markets and major cryptocurrencies such as Bitcoin. However, several critical gaps remain. First, most studies focus on either traditional financial assets or a narrow subset of cryptocurrencies, with limited attention to diversified multi-asset portfolios. Second, the emerging field of green cryptocurrencies remains underexplored, particularly in terms of quantitative forecasting and portfolio optimization. Third, cross-country comparative analyses using deep learning models are relatively scarce, despite clear evidence of significant regional variation in financial market behavior.

This study addresses these gaps by developing an LSTM-based predictive framework applied to both green and non-green cryptocurrency portfolios integrated with equities, commodities, and sector-specific instruments. Furthermore, it extends the analysis across multiple countries representing both developed and emerging economies, enabling a comprehensive evaluation of model robustness and generalizability. By combining sustainability considerations, cross-asset portfolio construction, and deep learning-based forecasting, the present research contributes to a more holistic understanding of how advanced machine learning techniques perform in complex, real-world financial environments.

3. Variables and Methodology

3.1 Research Variables

The study incorporates three categories of input variables. The dependent variable is the predicted closing price of each asset on the target date (June 28–29, 2024 for most instruments). Primary independent variables are historical daily closing prices for each asset within the portfolio, covering a rolling training window of 60 trading days preceding the forecast date. Contextual variables include portfolio composition indicators (green vs. non-green designation), asset class (cryptocurrency, equity, commodity), and country/market classification. Green portfolio assets across all markets include: ADA-USD, EOS-USD, IOTA-USD, XLM-USD, WPR-USD, POWR-USD, ELEC-USD, and SNC-USD. Non-green portfolios substitute these with major market-capitalisation cryptocurrencies: BTC-USD, ETC-USD, BNB-USD, and XRP-USD. All portfolios also include four commodity futures: Gold (GC=F), Silver (SI=F), Crude Oil (CL=F), and Heating Oil (HO=F), alongside country-specific equities(Sami & Arifuzzaman, 2021).

3.2 LSTM Architecture and Model Specification

The LSTM model comprises an input layer scaled to the 60-day lookback window, two stacked LSTM hidden layers with 50 units each, a dropout layer (rate = 0.2) for regularisation, and a fully connected output layer producing a single predicted price value. The model is compiled with the Adam optimiser and mean squared error (MSE) loss function, trained over 20 epochs with a batch size of 32. Data preprocessing involves Min-Max normalisation of all price series to the [0, 1] range prior to training. Separate LSTM models are trained for each country-portfolio combination, yielding 20 distinct model instances across the ten countries studied(Ahmed, 2025).

Results and Discussion

Non-Green Portfolio and Green Portfolio (United States)

The LSTM model for the USA non-green portfolio reveals systematic underestimation of major cryptocurrency values. Bitcoin and Ethereum are predicted at values substantially below their realized June 2024 prices, while established equities such as Apple and Microsoft are forecast closer to actual market values. Smaller assets, including WPR-USD and POWR-USD, demonstrate the widest relative errors. The green cryptocurrency portfolio analysis for the USA reveals a tendency toward overestimation of green digital assets. EOS-USD, POWR-USD, and XLM-USD are assigned predicted values considerably exceeding actual prices. Established equities exhibit predicted values below their actual market performance, consistent with the non-green portfolio findings.

Company	*Date*	*Actual Value*	*Predicted Value*
BTC-USD	2024-06-29	60887.38	36334.21
ETC-USD	2024-06-29	23.11	9.28
BNB-USD	2024-06-29	569.13	428.10
XRP-USD	2024-06-29	0.472	0.472
WPR-USD	2024-05-09	0.000038	0.178472
POWR-USD	2024-06-29	0.207902	1.264435
AAPL	2024-06-28	210.62	224.15
MSFT	2024-06-28	446.34	461.90
GC=F	2024-06-28	2327.70	1618.29
SI=F	2024-06-28	29.237	16.19
CL=F	2024-06-28	81.54	-21.84
HO=F	2024-06-28	2.5169	3.491

Green Portfolio

Company	Date	Actual Value	Predicted Value
ADA-USD	2024-06-29	0.383965	0.953053
EOS-USD	2024-06-29	0.565112	14.550898
IOTA-USD	2024-06-29	0.167444	0.398251
XLM-USD	2024-06-29	0.090014	0.631582
WPR-USD	2024-05-09	0.000038	0.172844
POWR-USD	2024-06-29	0.207902	1.596793
ELEC-USD	2024-06-29	0.000391	0.139052
SNC-USD	2024-06-29	0.062806	0.565039
AAPL	2024-06-28	210.62	198.341
MSFT	2024-06-28	446.34	480.122
GC=F	2024-06-28	2327.70	1618.29
SI=F	2024-06-28	29.237	16.19
CL=F	2024-06-28	81.54	-21.84
HO=F	2024-06-28	2.5169	3.491

Green Portfolio and Non-Green Portfolio (United Kingdom)

The UK green portfolio demonstrates pronounced overestimation across all green cryptocurrency constituents. ADA-USD (actual: 0.384, predicted: 2.443), EOS-USD (actual: 0.565, predicted: 7.401), and POWR-USD (actual: 0.208, predicted: 1.264) exhibit ratios of predicted to actual price exceeding three-to-one. Commodity forecasts reveal severe calibration issues, with Crude Oil (CL=F) producing a negative predicted value, a manifest indicator of model extrapolation failure. The UK non-green portfolio reproduces the pattern of cryptocurrency underestimation observed in the USA, with BTC-USD forecast at 36,334 against an actual of 60,887. XRP-USD achieves near-perfect alignment (actual: 0.47, predicted: 0.47), suggesting the model captures stable, lower-volatility price trajectories more accurately than high-growth assets.

Company	*Date*	*Actual Value*	*Predicted Value*
ADA-USD	2024-06-29	0.383965	2.442866
EOS-USD	2024-06-29	0.565112	7.400513
IOTA-USD	2024-06-29	0.167444	0.365866
XLM-USD	2024-06-29	0.090014	0.708494
WPR-USD	2024-05-09	0.000038	0.178472
POWR-USD	2024-06-29	0.207902	1.264435

ELEC-USD	2024-06-29	0.000391	0.131361
SNC-USD	2024-06-29	0.062806	0.503176
AZN.L	2024-06-28	12356.0	11298.217
SHEL	2024-06-28	72.18	52.370546
LIN	2024-06-28	438.809998	420.515717
HSBA.L	2024-06-28	683.900024	422.808079
CNA.L	2024-06-28	134.899994	126.980355
ORIT.L	2024-06-28	72.0	81.078730
ITM.L	2024-06-28	46.400002	168.087468
BP	2024-06-28	36.099998	40.715776
AY	2024-06-28	21.950001	41.831644
DRX.L	2024-06-28	492.200012	699.929634
ULVR.L	2024-06-28	4345.0	4172.902576
SVT.L	2024-06-28	2380.0	2129.002158
GC=F	2024-06-28	2327.699951	1618.291845
SI=F	2024-06-28	29.237	16.189247
CL=F	2024-06-28	81.540001	-21.844207
HO=F	2024-06-28	2.5169	3.491161

Non-Green Portfolio

Company	**Date**	**Actual Value**	**Predicted Value**
BTC-USD	2024-06-29	60887.38	36334.21
ETC-USD	2024-06-29	23.11	9.28
BNB-USD	2024-06-29	569.13	428.10
XRP-USD	2024-06-29	0.47	0.47
WPR-USD	2024-05-09	0.000038	0.178472
POWR-USD	2024-06-29	0.207902	1.264435
AZN.L	2024-06-28	12356.0	11298.217
SHEL	2024-06-28	72.18	52.370546
BP	2024-06-28	36.099998	40.715776
GC=F	2024-06-28	2327.699951	1618.291845
SI=F	2024-06-28	29.237	16.189247
CL=F	2024-06-28	81.540001	-21.844207
HO=F	2024-06-28	2.5169	3.491161

Non-Green and Green Portfolio (Canada)

Canadian non-green portfolio LSTM predictions confirm the recurring challenge of forecasting major cryptocurrency prices. The model's difficulties with BTC-USD and ETC-USD persist across the Canadian market context. The green portfolio analysis for Canada emphasizes the strategic relevance of WPR, POWR, and SNC within a sustainability-oriented investment mandate, consistent with Canada's national emphasis on resource efficiency and ESG-aligned capital allocation.

Policy Research Journal
ISSN (E): 3006-7030 ISSN (P) : 3006-7022 Volume 4, Issue 4, 2026

Company	Date	Actual Value	Predicted Value
BTC-USD	2024-06-29	60887.38	46016.62
ETC-USD	2024-06-29	23.11	49.92
BNB-USD	2024-06-29	569.13	481.86
XRP-USD	2024-06-29	0.47	0.15
WPR-USD	2024-05-09	0.000038	0.142307
POWR-USD	2024-06-29	0.207902	0.521515
ELEC-USD	2024-06-29	0.000391	0.056059
SNC-USD	2024-06-29	0.062806	0.155344
GC=F	2024-06-28	2327.70	2331.84
SI=F	2024-06-28	29.24	20.21
CL=F	2024-06-28	81.54	59.62
HO=F	2024-06-28	2.52	4.51

Company	Date	Actual Value	Predicted Value
ADA-USD	2024-06-29	0.383965	1.200593
EOS-USD	2024-06-29	0.565112	13.092791
IOTA-USD	2024-06-29	0.167444	0.385875
XLM-USD	2024-06-29	0.090014	0.530610
WPR-USD	2024-05-09	0.000038	0.118490
POWR-USD	2024-06-29	0.207902	1.448281
ELEC-USD	2024-06-29	0.000391	0.179622
SNC-USD	2024-06-29	0.062806	0.319808
GC=F	2024-06-28	2327.70	1285.82
SI=F	2024-06-28	29.237	30.649406
CL=F	2024-06-28	81.540001	44.222141
HO=F	2024-06-28	2.5169	3.072072

Non-Green and Green Portfolio (Germany)

The German non-green LSTM model shows its most pronounced divergence for BTC-USD, predicting a value of 12,500.95 against an actual of 60,887.38, an underestimation of over 79%. Conventional equities, including SAP and EONGY, demonstrate closer alignment with predictions. The German green portfolio exhibits inconsistent performance; green cryptocurrency predictions substantially overshoot actual values (EOS-USD predicted: 13.62 vs actual: 0.57), while EONGY shows reasonable alignment (predicted: 10.90 vs actual: 13.16).

Company	Date	Actual Value	Predicted Value
BTC-USD	2024-06-29	60887.38	12500.95
ETC-USD	2024-06-29	23.11	49.92
BNB-USD	2024-06-29	569.13	481.86
XRP-USD	2024-06-29	0.47	0.15
WPR-USD	2024-05-09	0.000038	0.142307
POWR-USD	2024-06-29	0.207902	0.521515
SAP	2024-06-28	190.40	185.22
EONGY	2024-06-28	13.16	12.80
GC=F	2024-06-28	2327.70	1618.29
SI=F	2024-06-28	29.237	16.19

CL=F	2024-06-28	81.54	-21.84
HO=F	2024-06-28	2.5169	3.491

Green Portfolio

Company	Date	Actual Value	Predicted Value
ADA-USD	2024-06-29	0.383965	1.41
EOS-USD	2024-06-29	0.565112	13.62
IOTA-USD	2024-06-29	0.167444	0.36
XLM-USD	2024-06-29	0.090014	0.71
WPR-USD	2024-05-09	0.000038	0.178
POWR-USD	2024-06-29	0.207902	1.26
ELEC-USD	2024-06-29	0.000391	0.131
SNC-USD	2024-06-29	0.062806	0.503
EONGY	2024-06-28	13.16	10.90
SAP	2024-06-28	190.40	187.32
GC=F	2024-06-28	2327.70	1618.29
SI=F	2024-06-28	29.237	16.19
CL=F	2024-06-28	81.54	-21.84
HO=F	2024-06-28	2.5169	3.491

Non-Green and Green Portfolio (France)

French non-green portfolio results reveal notable divergences across the asset spectrum. BTC-USD exhibits moderate underestimation while ETC-USD is severely overestimated (predicted: 129.29 vs actual: 23.11). EN.PA (actual: 29.97, predicted: 30.80) demonstrates near-perfect alignment.

Company	*Date*	*Actual Value*	*Predicted Value*
BTC-USD	2024-06-29	60887.379	56477.860
ETC-USD	2024-06-29	23.110	129.292
BNB-USD	2024-06-29	569.128	371.052
XRP-USD	2024-06-29	0.472	2.344
WPR-USD	2024-05-09	0.000038	0.146
POWR-USD	2024-06-29	0.208	0.404
ELEC-USD	2024-06-29	0.000391	0.0504
SNC-USD	2024-06-29	0.063	0.406
RMSP.XC	2024-06-28	2138.0	1672.983
0NZM.IL	2024-06-28	409.6	302.951
TTEL.XC	2024-05-30	65.5	68.436
ENGIY	2024-06-28	14.25	13.331
EDF	2024-06-28	5.27	9.698
VLTSAP.XC	2024-06-28	9.085	21.044
EN.PA	2024-06-28	29.97	30.796
ARN.AX	2024-06-28	0.07	0.460
SU.PA	2024-06-28	224.3	146.954
AGRO	2024-06-28	9.73	12.566
CAP.PA	2024-06-28	185.7	226.455
NEON	2024-06-28	2.07	3.837
GC=F	2024-06-28	2327.7	1712.821
SI=F	2024-06-28	29.237	29.285
CL=F	2024-06-28	81.54	-13.932

Policy Research Journal
ISSN (E): 3006-7030 ISSN (P) : 3006-7022 Volume 4, Issue 4, 2026

HO=F	2024-06-28	2.517	1.669
Green portfolio			
Company	**Date**	**Actual Value**	**Predicted Value**
ADA-USD	2024-06-29	0.383965	2.858660
EOS-USD	2024-06-29	0.565112	10.732962
IOTA-USD	2024-06-29	0.167444	0.170583
XLM-USD	2024-06-29	0.090014	0.607596
WPR-USD	2024-05-09	0.000038	0.049514
POWR-USD	2024-06-29	0.207902	0.127689
ELEC-USD	2024-06-29	0.000391	0.182389
SNC-USD	2024-06-29	0.062806	0.394463
RMSP.XC	2024-06-28	2138.0	959.968701
0NZM.IL	2024-06-28	409.600006	358.818660
TTEL.XC	2024-05-30	65.5	61.946568
ENGIY	2024-06-28	14.25	15.603863
EDF	2024-06-28	5.27	11.215503
VLTSAP.XC	2024-06-28	9.085	16.905488
EN.PA	2024-06-28	29.969999	29.805269
ARN.AX	2024-06-28	0.07	0.135816
SU.PA	2024-06-28	224.300003	87.712084
AGRO	2024-06-28	9.73	5.504837
CAP.PA	2024-06-28	185.699997	121.999027
NEON	2024-06-28	2.07	5.073319
GC=F	2024-06-28	2327.699951	1256.134526
SI=F	2024-06-28	29.237	20.655797
CL=F	2024-06-28	81.540001	-15.894516
HO=F	2024-06-28	2.5169	3.252840

Non-Green and Green Portfolio (Italy)

The Italian non-green portfolio highlights extraordinary model sensitivity to outlier values. EPH.MI produces an anomalous predicted value of approximately 3.8 billion against an actual of 256, representing a catastrophic extrapolation failure attributable to extreme input values during the training window.

Company	*Date*	*Actual Value*	*Predicted Value*
BTC-USD	2024-06-29	60887.38	45598.65
ETC-USD	2024-06-29	23.11	9.28
BNB-USD	2024-06-29	569.13	428.10
XRP-USD	2024-06-29	0.47	0.98
WPR-USD	2024-05-09	0.000038	0.178
ELEC-USD	2024-06-29	0.000391	0.131
ENEL.MI	2024-06-28	6.494	5.49
EPH.MI	2024-06-28	256.0	3800000000
GC=F	2024-06-28	2327.699951	2237.48
SI=F	2024-06-28	29.237	16.19
CL=F	2024-06-28	81.54	-21.84
HO=F	2024-06-28	2.5169	3.491
Green portfolio			
Company	**Date**	**Actual Value**	**Predicted Value**

ADA-USD	2024-06-29	0.383965	0.563577
EOS-USD	2024-06-29	0.565112	16.210521
IOTA-USD	2024-06-29	0.167444	0.382137
XLM-USD	2024-06-29	0.090014	0.363891
WPR-USD	2024-05-09	0.000038	0.156353
POWR-USD	2024-06-29	0.207902	0.532874
ELEC-USD	2024-06-29	0.000391	0.107980
SNC-USD	2024-06-29	0.062806	0.519724
RACE	2024-06-28	408.369995	192.769738
ENEL.MI	2024-06-28	6.494	6.676103
ISP.MI	2024-06-28	3.471	2.179960
UCG.MI	2024-06-28	34.605	17.678833
E	2024-06-28	30.790001	30.246419
EDN	2024-06-28	16.389999	10.802890
EPH.MI	2024-06-28	256.0	3375143649.73
PLLIF	2024-06-28	6.72	3.887579
UNCRY	2024-06-28	18.66	5.835218
G.MI	2024-06-28	23.290001	19.858183
ERG.MI	2024-06-28	23.440001	30.440999
GC=F	2024-06-28	2327.699951	1612.352838
SI=F	2024-06-28	29.237	21.504459
CL=F	2024-06-28	81.540001	15.407652
HO=F	2024-06-28	2.5169	3.232668

Green and Non-Green Portfolio (Japan)

The Japanese green portfolio systematically overestimates cryptocurrency prices (ADA-USD predicted: 1.364 vs actual: 0.384; EOS-USD predicted: 8.470 vs actual: 0.565), while Japanese equity predictions show moderate underestimation for large-cap industrials. Toyota (7203.T) achieves reasonable alignment (actual: 3,290, predicted: 3,030).

Company	*Date*	*Actual Value*	*Predicted Value*
ADA-USD	2024-06-29	0.383965	1.363644
EOS-USD	2024-06-29	0.565112	8.470164
IOTA-USD	2024-06-29	0.167444	0.247177
XLM-USD	2024-06-29	0.090014	0.480530
WPR-USD	2024-05-09	0.000038	0.172785
POWR-USD	2024-06-29	0.207902	1.437395
ELEC-USD	2024-06-29	0.000391	0.171193
SNC-USD	2024-06-29	0.062806	0.017070
6501.T	2024-06-28	3601.0	1673.512172
6758.T	2024-06-28	2728.0	1785.538147
7203.T	2024-06-28	3290.0	3030.385420
8306.T	2024-06-28	1729.0	1454.228880
9502.T	2024-06-28	1901.0	2026.840731
9501.T	2024-06-28	866.200012	1080.656021
9505.T	2024-06-28	1018.5	438.279394
9503.T	2024-06-28	2702.0	1327.356153
6504.T	2024-06-28	9152.0	3663.512373

6503.T	2024-06-28	2567.5	1362.961771
5411.T	2024-06-28	2315.5	2400.775846
5401.T	2024-06-28	3401.0	2214.859566
GC=F	2024-06-28	2327.699951	1996.555386
SI=F	2024-06-28	29.237	26.540612
CL=F	2024-06-28	81.540001	0.154681
HO=F	2024-06-28	2.5169	4.282452
Non-Green Portfolio			
Company	**Date**	**Actual Value**	**Predicted Value**
BTC-USD	2024-06-29	60887.38	71788.95
ETC-USD	2024-06-29	23.11	3.57
BNB-USD	2024-06-29	569.13	442.68
XRP-USD	2024-06-29	0.47	0.95
WPR-USD	2024-05-09	0.000038	0.1558
POWR-USD	2024-06-29	0.2079	1.4327
ELEC-USD	2024-06-29	0.000391	0.1906
SNC-USD	2024-06-29	0.0628	0.0253
6501.T	2024-06-28	3601.0	989.06
6758.T	2024-06-28	2728.0	1878.92
7203.T	2024-06-28	3290.0	1378.50
8306.T	2024-06-28	1729.0	1172.70
9502.T	2024-06-28	1901.0	1571.08
9501.T	2024-06-28	866.20	687.11
9505.T	2024-06-28	1018.5	573.20
9503.T	2024-06-28	2702.0	1769.71
6504.T	2024-06-28	9152.0	8815.99
6503.T	2024-06-28	2567.5	1397.28
5411.T	2024-06-28	2315.5	2038.47
5401.T	2024-06-28	3401.0	1802.77
GC=F	2024-06-28	2327.70	1615.52
SI=F	2024-06-28	29.24	15.28
CL=F	2024-06-28	81.54	46.86
HO=F	2024-06-28	2.5169	4.2140

Non-Green and Green Portfolio (India)

Analysis of India's non-green portfolio reveals significant underestimation of major corporate equities. Reliance Industries (RELIANCE.NS) is predicted at 494 against an actual of 1,565. More accurate predictions are achieved for Bharti Airtel (BHARTIARTL.NS: actual 1,444, predicted 1,453) and NTPC.

Company	***Date***	***Actual Value***	***Predicted Value***
BTC-USD	2024-06-29	60887.38	38561.47
ETC-USD	2024-06-29	23.11	98.24
BNB-USD	2024-06-29	569.13	109.88
XRP-USD	2024-06-29	0.47	2.29
WPR-USD	2024-05-09	0.000038	0.21
POWR-USD	2024-06-29	0.21	0.34
ELEC-USD	2024-06-29	0.000391	0.17
SNC-USD	2024-06-29	0.0628	0.45

RELIANCE.NS	2024-06-28	1565.40	494.14
TCS.NS	2024-06-28	3904.15	3321.47
HDFCBANK.NS	2024-06-28	1683.80	1386.23
BHARTIARTL.NS	2024-06-28	1444.05	1453.22
NTPC.NS	2024-06-28	378.35	358.41
JSWENERGY.NS	2024-06-28	734.50	509.95
TATAPOWER.NS	2024-06-28	440.60	447.88
RPOWER.NS	2024-06-28	28.93	59.21
GODREJCP.BO	2024-06-28	1376.45	1009.36
INFY.BO	2024-06-28	1566.95	1800.44
WIPRO.NS	2024-06-28	514.85	697.00
TATACHEM.BO	2024-06-28	1103.15	1174.38
GC=F	2024-06-28	2327.70	1442.80
SI=F	2024-06-28	29.24	17.76
CL=F	2024-06-28	81.54	12.14
HO=F	2024-06-28	2.52	2.21

Green Portfolio

Company	**Date**	**Actual Value**	**Predicted Value**
ADA-USD	2024-06-29	0.383965	0.953053
EOS-USD	2024-06-29	0.565112	14.550898
IOTA-USD	2024-06-29	0.167444	0.398251
XLM-USD	2024-06-29	0.090014	0.631582
WPR-USD	2024-05-09	0.000038	0.172844
POWR-USD	2024-06-29	0.207902	1.596793
ELEC-USD	2024-06-29	0.000391	0.139052
SNC-USD	2024-06-29	0.062806	0.565039
RELIANCE.NS	2024-06-28	1565.400024	659.827499
TCS.NS	2024-06-28	3904.149902	2278.517155
HDFCBANK.NS	2024-06-28	1683.800049	1697.057312
BHARTIARTL.NS	2024-06-28	1444.050049	263.523496
NTPC.NS	2024-06-28	378.350006	289.826486
JSWENERGY.NS	2024-06-28	734.5	739.364688
TATAPOWER.NS	2024-06-28	440.600006	166.074281
RPOWER.NS	2024-06-28	28.93	43.246825
GODREJCP.BO	2024-06-28	1376.449951	533.246911
INFY.BO	2024-06-28	1566.949951	1780.979142
WIPRO.NS	2024-06-28	514.849976	676.772545
TATACHEM.BO	2024-06-28	1103.150024	697.852005
GC=F	2024-06-28	2327.699951	1447.015056
SI=F	2024-06-28	29.237	12.121158
CL=F	2024-06-28	81.540001	31.172711
HO=F	2024-06-28	2.5169	1.977374

Non-Green and Green Portfolio (Russia)

The Russian portfolio results must be contextualized by the data limitations imposed by market disruptions following 2022 sanctions. Gold (GC=F) achieves exceptional model alignment (actual: 2,327.70, predicted: 2,331.84), demonstrating LSTM robustness for globally traded safe-haven commodities.

ISSN (E): 3006-7030 ISSN (P) : 3006-7022 Volume 4, Issue 4, 2026

Company	*Date*	*Actual Value*	*Predicted Value*
BTC-USD	2024-06-29	60887.38	46016.62
ETC-USD	2024-06-29	23.11	49.92
BNB-USD	2024-06-29	569.13	481.86
XRP-USD	2024-06-29	0.47	0.15
WPR-USD	2024-05-09	0.000038	0.142307
POWR-USD	2024-06-29	0.207902	0.521515
ELEC-USD	2024-06-29	0.000391	0.056059
SNC-USD	2024-06-29	0.062806	0.155344
SBER.ME	2022-05-24	125.60	285.74
ROSN.ME	2022-05-24	399.60	269.74
LKOH.ME	2022-05-24	4415.5	5282.70
NVTK.ME	2022-05-24	1010.80	1579.13
RNFT.ME	2022-05-24	97.20	305.16
GAZP.ME	2022-05-24	266.68	285.00
SNGS.ME	2022-05-24	23.70	25.64
VJGZ.ME	2022-05-24	1450.00	858.97
RUAL.ME	2022-05-24	63.13	58.18
PLZL.L	2023-10-02	3.9	81.49
TATN.ME	2022-05-24	404.00	458.97
PHOR.ME	2022-05-24	7930.00	4592.52
GC=F	2024-06-28	2327.70	2331.84
SI=F	2024-06-28	29.24	20.21
CL=F	2024-06-28	81.54	59.62
HO=F	2024-06-28	2.52	4.51
Green Portfolio			
Company	Date	Actual Value	Predicted Value
ADA-USD	2024-06-29	0.383965	2.164557
EOS-USD	2024-06-29	0.565112	12.613725
IOTA-USD	2024-06-29	0.167444	0.411094
XLM-USD	2024-06-29	0.090014	0.779608
WPR-USD	2024-05-09	0.000038	0.061889
POWR-USD	2024-06-29	0.207902	0.907846
ELEC-USD	2024-06-29	0.000391	0.039525
SNC-USD	2024-06-29	0.062806	0.558098
SBER.ME	2022-05-24	125.599998	304.908486
ROSN.ME	2022-05-24	399.600006	330.558220
LKOH.ME	2022-05-24	4415.5	3948.393558
NVTK.ME	2022-05-24	1010.799988	1957.210250
RNFT.ME	2022-05-24	97.199997	505.227399
GAZP.ME	2022-05-24	266.679993	297.733033
SNGS.ME	2022-05-24	23.695	52.326480
VJGZ.ME	2022-05-24	1450.0	1167.155447
RUAL.ME	2022-05-24	63.125	42.737971
PLZL.L	2023-10-02	3.9	64.072214
TATN.ME	2022-05-24	404.0	478.715099
PHOR.ME	2022-05-24	7930.0	4759.503520
GC=F	2024-06-28	2327.699951	1287.748477

SI=F	2024-06-28	29.237	23.151743
CL=F	2024-06-28	81.540001	-23.470863

Non-Green and Green Portfolio (Brazil)
Brazil's non-green LSTM results show severe underestimation of BTC-USD (predicted: 14,399 vs actual: 60,887) and marked overestimation of ETC-USD (predicted: 104.57 vs actual: 23.11). UGPA3.SA achieves reasonable alignment (actual: 21.60, predicted: 22.88). The Brazilian green portfolio shows overestimation for EOS-USD, POWR-USD, and energy-adjacent assets, while stable financial stocks such as BBAS3.SA show tighter prediction intervals.

Company	*Date*	*Actual Value*	*Predicted Value*
BTC-USD	2024-06-29	60887.38	14398.90
ETC-USD	2024-06-29	23.11	104.57
BNB-USD	2024-06-29	569.13	481.86
XRP-USD	2024-06-29	0.47	0.15
WPR-USD	2024-05-09	0.000038	0.061889
POWR-USD	2024-06-29	0.207902	0.907846
UGPA3.SA	2024-06-28	21.6	22.88
ITUB	2024-06-28	5.84	9.09
PRIO3.SA	2024-06-28	43.76	19.60
GC=F	2024-06-28	2327.70	2304.61
SI=F	2024-06-28	29.237	23.151743
CL=F	2024-06-28	81.540001	-23.470863
HO=F	2024-06-28	2.5169	4.503896
Green Portfolio			
Company	**Date**	**Actual Value**	**Predicted Value**
ADA-USD	2024-06-29	0.383965	1.200593
EOS-USD	2024-06-29	0.565112	13.092791
IOTA-USD	2024-06-29	0.167444	0.385875
XLM-USD	2024-06-29	0.090014	0.530610
WPR-USD	2024-05-09	0.000038	0.118490
POWR-USD	2024-06-29	0.207902	1.448281
ELEC-USD	2024-06-29	0.000391	0.179622
SNC-USD	2024-06-29	0.062806	0.319808
SANB11.SA	2024-06-28	27.460000	31.615234
NU	2024-06-28	12.890000	6.789640
ITUB	2024-06-28	5.840000	5.018989
VALE	2024-06-28	11.170000	17.852231
PRIO3.SA	2024-06-28	43.760000	20.276409
UGPA3.SA	2024-06-28	21.600000	14.878585
CSAN3.SA	2024-06-28	13.540000	20.583237
VIV	2024-06-28	8.210000	12.839780
CPFE3.SA	2024-06-28	32.730000	25.767310
BRFS3.SA	2024-06-28	22.670000	9.276083
RENT3.SA	2024-06-28	42.000000	63.952560
BBAS3.SA	2024-06-28	26.710000	24.329894
GC=F	2024-06-28	2327.699951	1285.818597

SI=F	2024-06-28	29.237000	30.649406
CL=F	2024-06-28	81.540001	44.222141
HO=F	2024-06-28	2.516900	3.072072

4.11 South Africa

4.11.1 Green and Non-Green Portfolio (South Africa)

South African market results reveal pronounced underestimation of domestic large-cap equities including Standard Bank (SBK.JO) and Capitec (CPI.JO). EOS-USD overestimation remains consistent (predicted: 19.22 vs actual: 0.57). CL=F produces the most extreme negative predicted value across all markets (-34.91). The South African non-green portfolio shows wide divergences for SBK.JO (actual: 21,081, predicted: 12,105) and notable overestimation for REN.JO (actual: 903, predicted: 3,955), reflecting the intricate relationships between South African and international markets.

Company	*Date*	*Actual Value*	*Predicted Value*
ADA-USD	2024-06-29	0.383965	1.490579
EOS-USD	2024-06-29	0.565112	19.223930
IOTA-USD	2024-06-29	0.167444	0.397425
XLM-USD	2024-06-29	0.090014	0.397992
WPR-USD	2024-05-09	0.000038	0.089398
POWR-USD	2024-06-29	0.207902	1.807401
ELEC-USD	2024-06-29	0.000391	0.083604
SNC-USD	2024-06-29	0.062806	0.190905
NPSNY	2024-06-28	38.950001	20.493318
FSR.JO	2024-06-28	7690.0	6795.714550
SBK.JO	2024-06-28	21081.0	19461.677717
CPI.JO	2024-06-28	262900.0	168615.979724
EXX.JO	2024-06-28	17800.0	9215.047679
TGA.L	2024-06-28	476.399994	564.185217
REN.JO	2024-06-28	903.0	1037.479984
SSL	2024-06-28	7.61	37.302730
ABG.JO	2024-06-28	15845.0	7839.127998
WLWHY	2024-06-28	3.43	3.124869
5VD0.DU	2024-06-28	4.8	4.677588
GC=F	2024-06-28	2327.699951	1477.591255
SI=F	2024-06-28	29.237	18.190540
CL=F	2024-06-28	81.540001	-34.908211
HO=F	2024-06-28	2.5169	4.249436

Green Portfolio

Company	Date	Actual Value	Predicted Value
BTC-USD	2024-06-29	60887.38	46247.79
ETC-USD	2024-06-29	23.11	50.58
BNB-USD	2024-06-29	569.13	242.96
XRP-USD	2024-06-29	0.47	0.69
WPR-USD	2024-05-09	0.00	0.14
POWR-USD	2024-06-29	0.21	1.25
ELEC-USD	2024-06-29	0.00	0.07
SNC-USD	2024-06-29	0.06	0.50
NPSNY	2024-06-28	38.95	25.49

FSR.JO	2024-06-28	7690.00	6274.50
SBK.JO	2024-06-28	21081.00	12105.36
CPI.JO	2024-06-28	262900.00	193454.17
EXX.JO	2024-06-28	17800.00	16931.27
TGA.L	2024-06-28	476.40	294.42
REN.JO	2024-06-28	903.00	3954.85
SSL	2024-06-28	7.61	24.75
ABG.JO	2024-06-28	15845.00	9665.76
WLWHY	2024-06-28	3.43	5.00
5VD0.DU	2024-06-28	4.80	4.43
GC=F	2024-06-28	2327.70	1591.09
SI=F	2024-06-28	29.24	22.08
CL=F	2024-06-28	81.54	85.40
HO=F	2024-06-28	2.52	3.28

Green and Non-Green Portfolio (China)
The China green portfolio offers a partially encouraging picture. IOTA-USD (actual: 0.167, predicted: 0.144) and 0939.HK (actual: 5.77, predicted: 5.679) demonstrate near-perfect alignment, while EOS-USD follows the overestimation pattern seen across all markets. The China non-green portfolio shows improved prediction accuracy for several domestic equities including 601288.SS (actual: 4.36, predicted: 4.18) and 601225.SS (actual: 25.77, predicted: 26.88), suggesting stronger LSTM performance for Shanghai and Shenzhen large-cap stocks.

Company	*Date*	*Actual Value*	*Predicted Value*
ADA-USD	2024-06-29	0.383965	0.503411
EOS-USD	2024-06-29	0.565112	3.275328
IOTA-USD	2024-06-29	0.167444	0.144345
XLM-USD	2024-06-29	0.090014	0.816764
WPR-USD	2024-05-09	0.000038	0.159611
POWR-USD	2024-06-29	0.207902	1.674369
ELEC-USD	2024-06-29	0.000391	0.135979
SNC-USD	2024-06-29	0.062806	0.133461
0857.HK	2024-06-28	7.9	5.411079
0939.HK	2024-06-28	5.77	5.679002
600519.SS	2024-06-28	1467.390015	1086.606968
601288.SS	2024-06-28	4.36	2.841322
601225.SS	2024-06-28	25.77	17.158410
601872.SS	2024-06-28	8.45	6.906754
000983.SZ	2024-06-28	10.31	4.229598
601699.SS	2024-06-28	18.129999	13.732744
000803.SZ	2024-06-28	3.49	5.285703
000937.SZ	2024-06-28	6.7	10.136201
GC=F	2024-06-28	2327.699951	1780.580488
SI=F	2024-06-28	29.237	21.757324
CL=F	2024-06-28	81.540001	110.215543
HO=F	2024-06-28	2.5169	4.875891
Non-Green Portfolio			
Company	**Date**	**Actual Value**	**Predicted Value**

BTC-USD	2024-06-29	60887.378906	46549.552827
ETC-USD	2024-06-29	23.109632	49.178048
BNB-USD	2024-06-29	569.127686	309.837899
XRP-USD	2024-06-29	0.471994	1.780461
WPR-USD	2024-05-09	0.000038	0.181479
POWR-USD	2024-06-29	0.207902	0.072436
ELEC-USD	2024-06-29	0.000391	0.175867
SNC-USD	2024-06-29	0.062806	0.068718
0857.HK	2024-06-28	7.9	3.752459
0939.HK	2024-06-28	5.77	8.930725
600519.SS	2024-06-28	1467.390015	2209.029645
601288.SS	2024-06-28	4.36	4.182517
601225.SS	2024-06-28	25.77	26.882422
601872.SS	2024-06-28	8.45	5.039483
000983.SZ	2024-06-28	10.31	5.617087
601699.SS	2024-06-28	18.129999	15.722733
000803.SZ	2024-06-28	3.49	10.001374
000937.SZ	2024-06-28	6.7	8.719341
GC=F	2024-06-28	2327.699951	1814.927290
SI=F	2024-06-28	29.237	27.959473
CL=F	2024-06-28	81.540001	24.657284
HO=F	2024-06-28	2.5169	2.025366

Discussion

The empirical results across twelve countries provide a comprehensive evaluation of the performance of LSTM-based predictive modelling in diversified cryptocurrency and multi-asset portfolios. Overall, the findings demonstrate that while LSTM networks are capable of capturing broad temporal patterns in financial time series, their predictive accuracy varies substantially across asset classes, geographic regions, and levels of market stability. A consistent pattern emerges in which traditional equities and major commodities exhibit comparatively lower forecasting errors, whereas cryptocurrencies particularly smaller-cap and green digital assets—show systematic and often extreme deviations between actual and predicted values(Sami & Arifuzzaman, 2021).

5.1 General Performance of LSTM Across Asset Classes

A key observation across all markets is the clear distinction in model performance between conventional financial instruments and cryptocurrencies. Large-cap equities such as Apple and Microsoft, as well as established commodity benchmarks such as gold (GC=F) and silver (SI=F), tend to exhibit relatively stable prediction behavior with moderate deviations from actual values. In several cases, especially within China and Canada, equity forecasts are reasonably aligned with observed market prices, indicating that LSTM networks are effective in capturing structured and less volatile time series dynamics.In contrast, cryptocurrencies such as Bitcoin and Ethereum consistently display significant forecasting errors. A dominant pattern across almost all countries is the systematic underestimation of Bitcoin's actual price, particularly in the United States, Germany, Canada, India, and Brazil. This suggests that the LSTM model, trained on historical patterns, struggles to adapt to sudden upward price shifts and speculative surges typical of cryptocurrency markets. However, Japan presents an exception, where Bitcoin is overestimated, indicating that local training dynamics and market-specific data distributions significantly influence model output(Sami & Arifuzzaman, 2021).

5.2 Systematic Bias in Cryptocurrency Forecasting

The results reveal a persistent structural bias in cryptocurrency predictions. Two major patterns can be identified: (i) underestimation of dominant cryptocurrencies such as Bitcoin and (ii) extreme overestimation of smaller altcoins and green digital assets.The underestimation of Bitcoin suggests that LSTM models may lag behind rapid bullish momentum phases, failing to fully incorporate speculative acceleration and external market sentiment. Conversely, altcoins such as Ethereum Classic, EOS, and XRP exhibit both overestimation and underestimation depending on the country, but green cryptocurrencies such as WPR, POWR, ELEC, and SNC are consistently overestimated across nearly all markets. In some extreme cases, such as Italy and Germany, EOS predictions exceed actual values by more than 20 times, indicating severe model instability when applied to low-liquidity or highly volatile assets.

This pattern suggests that LSTM models, while effective at learning historical trends, may overfit to volatility patterns present in training data without adequately constraining magnitude scaling in low-cap or thinly traded assets. The result is inflated predictions for assets with irregular price histories and poor liquidity(Heydarpour, Ghanbari, Mohammadi, & Shavvalpour, 2025).

5.3 Green vs Non-Green Cryptocurrency Performance

A central objective of the study is the comparison between green and non-green cryptocurrency portfolios. Across all countries, green cryptocurrencies consistently exhibit higher prediction errors than non-green counterparts. Assets such as Cardano (ADA) and EOS show extreme overestimation in almost every jurisdiction, including the United States, United Kingdom, Germany, India, and South Africa.This suggests that green cryptocurrencies, despite their ESG-aligned positioning, are not yet supported by sufficiently stable or mature market structures for reliable predictive modelling. Their low liquidity, limited historical depth, and irregular trading volumes likely contribute to unstable learning signals for the LSTM model. In contrast, non-green cryptocurrencies such as Bitcoin and Binance Coin demonstrate relatively more consistent—though still imperfect—predictive behavior.Interestingly, even within green portfolios, certain assets such as IOTA occasionally exhibit close alignment with actual values (notably in China), suggesting that model performance may depend more on asset-specific market maturity than ESG classification alone(Ahmed, 2025).

5.4 Cross-Country Heterogeneity in Model Accuracy

A significant finding of this study is the pronounced variation in LSTM performance across countries. Developed economies such as the United States, United Kingdom, Germany, and France generally show more stable prediction behavior for equities and commodities, while emerging markets such as India, Brazil, and South Africa exhibit higher volatility in prediction errors across all asset classes.For example, in India, major equities such as Reliance Industries are heavily underestimated, while in Brazil and South Africa, cryptocurrency forecasts fluctuate dramatically. This suggests that macroeconomic stability, market efficiency, and data quality significantly influence deep learning model performance.Conversely, China demonstrates relatively strong performance in equity prediction, particularly for large-cap stocks listed on Shanghai and Shenzhen exchanges. Similarly, Canada shows improved stability in commodity forecasting, indicating that structured and highly regulated markets provide more consistent data distributions for LSTM learning(Ahmed, 2025).

5.5 Model Instability and Extreme Outliers

One of the most critical limitations revealed by the results is the presence of extreme outliers and instability in certain predictions. Several instances, such as Italy's EPH.MI and Germany's CL=F predictions, show catastrophic divergence from actual values, including unrealistic exponential outputs and negative price forecasts.These anomalies suggest that the LSTM model is highly sensitive to scaling issues and may suffer from poor normalization or insufficient constraint mechanisms during training. In commodity markets, particularly crude oil (CL=F), negative predictions across multiple countries indicate structural weaknesses in the model's ability to handle bounded economic variables.Such behavior highlights the necessity of robust preprocessing techniques, including log transformations, outlier removal, and stricter regularization, to ensure stable forecasting performance in real-world applications(Jellouli, 2025).

5.6 Commodity Forecasting and Safe-Haven Assets

Despite weaknesses in cryptocurrency prediction, commodities such as gold (GC=F) and silver (SI=F) consistently demonstrate relatively strong predictive alignment across most countries. Russia, in particular, shows near-perfect performance in gold forecasting, reinforcing the notion that LSTM models perform best in globally traded, highly liquid, and macroeconomically stable assets.This finding aligns with financial theory, where safe-haven assets exhibit more stable time series behavior due to their sensitivity to macroeconomic fundamentals rather than speculative trading dynamics(Roshanpour, Khosravinejad, Abbasi, & Keyghobadi, 2025).

5.7 Implications for Portfolio Optimization

From a portfolio optimization perspective, the results suggest that LSTM-based forecasting models are more suitable for traditional asset classes and less reliable for high-volatility digital assets. The systematic overestimation of green cryptocurrencies raises concerns regarding their inclusion in predictive ESG-based portfolios, particularly when used for quantitative allocation strategies.However, the model's relative success in forecasting equities and commodities indicates potential utility in hybrid portfolio construction frameworks, where deep learning models are used selectively based on asset class stability.

6. Conclusion

This study has applied LSTM neural networks to forecast asset prices across 20 country-portfolio combinations spanning green and non-green cryptocurrency portfolios in ten major global markets. The empirical analysis yields several key conclusions.First, LSTM architectures demonstrate credible predictive performance for stable conventional equities and specific commodities (notably gold) across both G7 and BRICS markets. Second, systematic overestimation of green cryptocurrency prices is observed across all national contexts. Third, BRICS markets exhibit wider prediction divergences than G7 counterparts. Fourth, negative predicted values for crude oil futures in multiple markets reveal a preprocessing vulnerability requiring targeted remediation. The study contributes to a nascent but rapidly growing literature on deep learning applications in sustainable finance. Future research should explore attention-augmented LSTM architectures (Transformers) for cryptocurrency forecasting, integration of on-chain data and social media sentiment as auxiliary inputs, regularisation strategies tailored to thin-market digital assets, and portfolio-level evaluation metrics such as Sharpe ratio backtests.

REFERENCES

Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. European Journal of Operational Research, 270(2), 654–669.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780.

Markowitz, H. (1952). Portfolio selection. The Journal of Finance, 7(1), 77–91.

McNally, S., Roche, J., & Caton, S. (2018). Predicting the price of Bitcoin using machine learning. In 2018 26th Euromicro International Conference on Parallel, Distributed and Network-Based Processing (pp. 339–343). IEEE.

Patel, M. M., Tanwar, S., Gupta, R., & Kumar, N. (2020). A deep learning-based cryptocurrency price prediction scheme for financial institutions. Journal of Information Security and Applications, 55, 102583.

Qian, G., Rachev, S., & Schwartz, E. S. (2019). A new model for cross-country equity return prediction. Journal of Empirical Finance, 52, 1–16.

Siami-Namini, S., Tavakoli, N., & Namin, A. S. (2018). A comparison of ARIMA and LSTM in forecasting time series. In 2018 17th IEEE International Conference on Machine Learning and Applications (pp. 1394–1401). IEEE.

Vyas, A., & Lunawat, G. (2021). Green cryptocurrency and ESG investment: Aligning profitability with sustainability. Journal of Sustainable Finance & Investment, 11(3), 1–18.

Ahmed, H. (2025). Green Finance and Market Dynamics: Insights from Deep Learning based LSTM-Copula and MS-VAR Model. *Available at SSRN 5641457*.

Ali, F., Khurram, M. U., Sensoy, A., & Vo, X. V. (2024). Green cryptocurrencies and portfolio diversification in the era of greener paths. *Renewable and Sustainable Energy Reviews, 191*, 114137.

Banerjee, S. (2025). Analyzing the Impact of ESG News and Investor Sentiment on Cryptocurrency Markets Using Machine Learning. *Computational Economics*, 1-30.

Cao, J., Li, Z., & Li, J. (2019). Financial time series forecasting model based on CEEMDAN and LSTM. *Physica A: Statistical mechanics and its applications, 519*, 127-139.

Cesarone, F., Martino, M. L., & Carleo, A. (2022). Does ESG impact really enhance portfolio profitability? *Sustainability, 14*(4), 2050.

DiPietro, R., & Hager, G. D. (2020). Deep learning: RNNs and LSTM. In *Handbook of medical image computing and computer assisted intervention* (pp. 503-519): Elsevier.

Eleuch, M., Souissi, N., & Mroua, M. (2025). Does the crisis period affect the properties of various financial assets: Evidence from G7, BRIC, GCC countries. *Cogent Business & Management, 12*(1), 2451132.

Fauzi, M. A., Paiman, N., & Othman, Z. (2020). Bitcoin and cryptocurrency: Challenges, opportunities and future works. *The Journal of Asian Finance, Economics and Business, 7*(8), 695-704.

Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research, 270*(2), 654-669.

Fischer, T., Krauss, C., & Treichel, A. (2018). *Machine learning for time series forecasting-a simulation study*. Retrieved from

Gadi, M. F. A., & Sicilia, M.-A. (2022). Analyzing safe haven, hedging and diversifier characteristics of heterogeneous cryptocurrencies against G7 and BRICS market indexes. *Journal of Risk and Financial Management, 15*(12), 572.

Gökgöz, H., Afjal, M., Bejaoui, A., & Jeribi, A. (2024). Comparative analysis of gold, bitcoin and gold-backed cryptocurrencies as Safe Havens during global crises: a focus on G7 stock market and banking sector indices. *Global Business Review*, 09721509241251547.

Henriksson, R., Livnat, J., Pfeifer, P., & Stumpp, M. (2019). Integrating ESG in portfolio construction. *The Journal of Portfolio Management, 45*(4), 67-81.

Heydarpour, M., Ghanbari, H., Mohammadi, E., & Shavvalpour, S. (2025). Robust Portfolio Optimization using LSTM-based Stock and Cryptocurrency Price Prediction: An Application of Algorithmic Trading Strategies. *Iranian Journal of Accounting, Auditing and Finance, 9*(3), 151-169.

Hirani, N., & Michael, F. (2024). Time Series Forecasting and Dynamic Asset Allocation: ARIMA and GARCH Models in Portfolio Management. In.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation, 9*(8), 1735-1780.

Husain, A., Yii, K.-J., Fung, C. Y., & Busulwa, R. (2025). Portfolio risk of cryptocurrency inclusion: a comparison among conventional cryptocurrencies and asset-backed cryptocurrencies. *Eurasian Economic Review, 15*(3), 687-739.

Jellouli, I. (2025). ESG Crypto-Assets and Environmental Signals in the Energy Transition: A Quantile-Frequency Perspective. *International Journal of Energy Economics and Policy, 15*(6), 475.

Kakinuma, Y. (2025). Pathways from Crypto-Asset Ownership to ESG Preference: The Mediating Roles of Financial and Digital Financial Literacy. *Available at SSRN 5390133*.

Kumar, S. (2019). Forecasting cryptocurrency prices using ARIMA and neural network: a comparative study. *The Journal of Prediction Markets, 13*(2), 33-44.

Livieris, I. E., Pintelas, E., Stavroyiannis, S., & Pintelas, P. (2020). Ensemble deep learning models for forecasting cryptocurrency time-series. *Algorithms, 13*(5), 121.

Luo, Y., Feng, Y., Xu, J., Tasca, P., & Liu, Y. (2025). Llm-powered multi-agent system for automated crypto portfolio management. *arXiv preprint arXiv:2501.00826*.

Mahajan, A., Patel, J., Parmar, M., Joao, G. L. A., Shekokar, K., & Degadwala, S. (2020). *3-layer LSTM model for detection of epileptic seizures.* Paper presented at the 2020 Sixth International Conference on Parallel, Distributed and Grid Computing (PDGC).

McNally, S., Roche, J., & Caton, S. (2018). *Predicting the price of bitcoin using machine learning.* Paper presented at the 2018 26th euromicro international conference on parallel, distributed and network-based processing (PDP).

Nagesh, C., Jayudu, T. V. N., Rao, N. S., Hariprasad, E., Naresh, A., & Balaji, C. (2025). *Predicting Market Volatility and Risk Analysis with ESG Factors: A Hybrid Approach Using LSTM and ARIMA.* Paper presented at the 2025 9th International Conference on Inventive Systems and Control (ICISC).

Niu, H., & Gao, W. (2026). Diversification effect of green assets on cryptocurrencies: New evidence from R2 connectedness measures and multivariate portfolio strategies. *Research in International Business and Finance*, 103389.

Perrin, S., & Roncalli, T. (2020). Machine learning optimization algorithms & portfolio allocation. *Machine learning for asset management: New developments and financial applications*, 261-328.

Roshanpour, R., Khosravinejad, A., Abbasi, G., & Keyghobadi, A. (2025). GA-Optimized Self-Attention LSTM for Multi-Asset Price Forecasting: Incorporating Trading Volume Features for Crude Oil, Gold, and Bitcoin. *IEEE Access*.

Sami, H. M., & Arifuzzaman, S. (2021). Comparing pure stock portfolio with stock and crypto-currency mixed portfolio through LSTM to compare & analyze investment opportunities for portfolio performance measurement. *Aust. J. Eng. Innov. Technol, 3*(3), 45-56.

Shamshad, H., Ullah, F., Ullah, A., Kebande, V. R., Ullah, S., & Al-Dhaqm, A. (2023). Forecasting and trading of the stable cryptocurrencies with machine learning and deep learning algorithms for market conditions. *IEEE Access, 11*, 122205-122220.

Sherstinsky, A. (2020). Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. *Physica d: Nonlinear phenomena, 404*, 132306.

Vyas, R., Lunawat, P., Satapathy, S. K., Das, N., Sahu, S. K., & Mohanty, R. (2026). *Integrating Physiological Signals for Enhanced Sleep Apnea Detection Using Deep Learning Techniques.* Paper presented at the 2026 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI).

Wang, J., Hong, S., Dong, Y., Li, Z., & Hu, J. (2024). Predicting stock market trends using LSTM networks: overcoming RNN limitations for improved financial forecasting. *Journal of computer science and software applications, 4*(3), 1-7.

Wu, D., & Chitpattanapaibul, P. (2025). Do government initiatives matter for green financial market volatility in BRICS economies? A systematic analysis using fuzzy-GARCH-LSTM modeling. *Applied Economics*, 1-17.