Forecasting Bitcoin's Impact on Gold and Clean Energy Returns with Advanced Machine Learning

Abstract

Motivated by the increasing prominence of cryptocurrencies and their potential impact on traditional and renewable energy assets, this research aims to uncover the extent and nature of Bitcoin's influence on these critical financial sectors. The study employs various advanced analytical methods, including Vector Autoregression (VAR), Dynamic Time Warping (DTW), and Random Forest (RF) to analyze the relationships and predict future returns. The findings indicate that Bitcoin exhibits high volatility and distinct market behavior compared to gold and clean energy assets, with moderate correlations particularly observed with solar and wind energy. The VAR and RF models demonstrate effectiveness in capturing general trends during stable periods but struggle with high volatility, highlighting the challenges in forecasting Bitcoin's returns. DTW results show that Bitcoin has the closest temporal alignment with solar energy, suggesting some interconnectedness driven by broader market trends. These insights highlight Bitcoin's potential as a diversifying asset for investors, the need for tailored regulatory frameworks for policymakers, and opportunities for the academic community to explore the complex dynamics between cryptocurrencies and other financial markets.

Keywords: *Bitcoin; Machine Learning; Gold Returns; Clean Energy Markets; Financial Forecasting*

1.0 Introduction

In recent years, the financial landscape has seen significant transformations, with cryptocurrencies like Bitcoin gaining widespread attention. The volatile nature of Bitcoin and its speculative trading has led to its inclusion in many investment portfolios as a potential high-risk, high-reward asset. Additionally, the global shift towards clean energy has seen increased investment in renewable energy sources such as solar and wind power. As nations strive to meet their carbon reduction goals, the financial markets for these clean energy technologies are becoming increasingly vital. Recent developments, such as the growing institutional adoption of Bitcoin and policy measures promoting clean energy investments, underscore the interconnectedness of these markets. For instance, the surge in Bitcoin prices in late 2020 and early 2021 and the subsequent volatility have sparked debates about its role as a store of value and its environmental impact due to energy-intensive mining processes (Meyer, 2021; Smith, 2021).

Recent news and developments further highlight the relevance of this study. For example, Tesla's announcement in early 2021 of its $1.5 billion investment in Bitcoin and its brief acceptance of Bitcoin as payment for its electric vehicles brought significant attention to the intersection of cryptocurrencies and clean energy (BBC, 2021). This move not only influenced Bitcoin's price but also sparked debates about the environmental implications of Bitcoin mining, given its high energy consumption and carbon footprint. Such events underscore the importance of understanding the interplay between Bitcoin and clean energy markets, as decisions by major corporations can have far-reaching impacts on both sectors. Moreover, the increasing regulatory scrutiny of cryptocurrencies adds another layer of complexity to this analysis. Governments worldwide are grappling with how to regulate Bitcoin and other cryptocurrencies to prevent financial crimes while fostering innovation. In 2021, China intensified its crackdown on cryptocurrency mining and trading, citing environmental concerns and financial stability risks (Bloomberg, 2021). These regulatory developments can significantly influence Bitcoin's market dynamics and its interactions with other assets, making it crucial to incorporate these factors into the analysis. In addition to regulatory issues, the financial markets have seen a growing trend of incorporating Environmental, Social, and Governance (ESG) criteria into investment decisions. Investors are increasingly aware of the environmental impact of their investments, which has led to a surge in demand for green bonds and renewable energy assets.

Bitcoin's environmental impact has become a topic of significant concern and debate, particularly due to the energy-intensive process of Bitcoin mining. Recent reports have highlighted that Bitcoin mining consumes more electricity annually than some entire countries, such as Argentina (BBC, 2021). This high energy consumption is primarily driven by the Proof of Work (PoW) consensus mechanism, which requires vast amounts of computational power. A study by the University of Cambridge estimated that Bitcoin's annual carbon footprint is comparable to that of New Zealand, producing around 37 megatons of CO_2 annually (Cambridge Centre for Alternative Finance, 2021). This has prompted reactions from various stakeholders, including major corporations. For instance, Tesla's CEO Elon Musk announced in May 2021 that the company would suspend vehicle purchases using Bitcoin due to environmental concerns, highlighting the need for sustainable energy solutions in cryptocurrency mining (Reuters, 2021). These developments underscore the critical need for the cryptocurrency industry to explore more environmentally friendly alternatives, such as transitioning to renewable energy sources or adopting less energy-intensive consensus mechanisms like Proof of Stake (PoS). The environmental footprint of Bitcoin not only influences its market dynamics but also intersects with broader discussions on sustainability and climate change mitigation.

Despite the burgeoning interest in both Bitcoin and clean energy markets, there remains a significant gap in understanding how these two sectors influence each other. The existing literature primarily focuses on the independent analysis of cryptocurrencies and renewable energy markets. Studies on Bitcoin often concentrate on its price dynamics, volatility, and regulatory challenges (Nakamoto, 2008; Baur et al., 2018), while research on clean energy markets typically examines investment trends, policy impacts, and technological advancements (IEA, 2020; REN21, 2021). However, there is a paucity of research that explores the potential interdependencies between Bitcoin and clean energy returns, particularly in the context of advanced machine learning techniques. This gap is critical as understanding these relationships could inform more effective investment strategies and policy decisions.

To address this gap, this study poses several research questions aimed at elucidating the relationships between Bitcoin, gold, and clean energy markets:

1. How does Bitcoin's price volatility impact the returns of gold and clean energy assets?

2. What are the predictive capabilities of advanced machine learning models in forecasting the returns of Bitcoin, gold, and clean energy assets?

3. Are there significant correlations between Bitcoin and various clean energy markets, such as solar, wind, and bioclean fuel?

4. How do shocks to Bitcoin prices influence the returns of gold and clean energy assets over time?

5. Can Bitcoin be considered a diversifying asset within portfolios that include traditional and clean energy investments?

6. How do policy changes and market developments in the clean energy sector affect Bitcoin's market behavior?

7. What are the implications of Bitcoin’s market dynamics for sustainable investment strategies?

The application of machine learning techniques in financial forecasting offers several advantages for this study. Traditional econometric models often struggle with the high volatility and non-linear relationships characteristic of financial markets (Atsalakis & Valavanis, 2009). Machine learning models, such as Random Forest (RF), Vector Autoregression (VAR), and Dynamic Time Warping (DTW), can handle large datasets, capture complex patterns, and provide more accurate forecasts (Krollner et al., 2010; Chong et al., 2017). These techniques are particularly useful for analyzing the volatile nature of Bitcoin and its interactions with other assets. By leveraging these advanced methods, this study aims to provide more reliable predictions and insights into the interdependencies between Bitcoin, gold, and clean energy returns.

This study distinguishes itself from earlier literature by integrating advanced machine learning techniques to explore the dynamic relationships between Bitcoin, gold, and clean energy markets. While previous studies have primarily focused on the independent analysis of these assets, this research adopts a holistic approach to examine their interconnectedness. By doing so, it addresses the gaps in existing literature and provides a comprehensive understanding of how Bitcoin's market behavior impacts and is impacted by traditional and renewable energy markets. The findings from this study are expected to offer valuable insights for investors seeking to diversify their portfolios, policymakers aiming to regulate cryptocurrency markets effectively, and academics exploring the complex dynamics of modern financial markets.

Forecasting Bitcoin's impact on gold and clean energy returns using advanced machine learning is crucial because it addresses a significant gap in the current financial research landscape, which often treats these assets in isolation. Given Bitcoin's volatile nature and its growing influence in global markets, understanding its interactions with traditional and renewable energy assets is vital for comprehensive risk management and strategic investment planning. Machine learning techniques, such as Random Forest, Vector Autoregression (VAR), and Dynamic Time Warping (DTW), offer sophisticated tools to capture complex patterns and relationships that traditional econometric models might miss. This study enhances predictability by leveraging these advanced methods to provide more accurate and nuanced forecasts, helping investors make informed decisions and manage risks effectively. Moreover, it informs policymakers about potential systemic risks and opportunities, guiding the development of more robust regulatory frameworks. By filling this gap, the research contributes to a deeper understanding of how cryptocurrency dynamics influence other critical sectors, promoting more integrated and forward-looking financial analyses.

2.0 Data and Methodology

This study employs a comprehensive methodology to explore Bitcoin's impact on gold and clean energy returns using advanced machine learning techniques. The methodology encompasses data collection, preprocessing, model development, and evaluation phases. Each step is described in detail below, including the techniques and equations used for the analysis.

2.1. Data Collection and Preprocessing

The first step involves collecting historical financial data for Bitcoin, gold, and various clean energy assets including solar energy, wind energy, and bio-clean fuel. The data spans from January 2015 to December 2022, covering daily closing prices for Bitcoin, gold, and clean energy assets, as well as the Volatility Index (VIX) as a measure of market uncertainty. The data is sourced from reputable financial databases such as Yahoo Finance and the World Bank for the clean energy indices. The preprocessing steps involve cleaning the data to handle missing values, ensuring consistency in time series intervals, and normalizing the data to make it suitable for analysis. The normalization is performed using the formula:

$$X_t = (X_t - \bar{X}) / \sigma_X$$

where X_t is the price at time t, $\bar{X}$ is the mean price, and σ_X is the standard deviation of prices.

2.2. Vector Autoregression (VAR) Model

The VAR model is employed to capture the linear relationships between Bitcoin prices, gold returns, and clean energy returns. The VAR model is expressed as:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + ... + A_p Y_{t-p} + B + \varepsilon_t$$

where Y_t is a vector of endogenous variables (Bitcoin, Gold, Clean Energy Returns), A_i are matrices of coefficients, p is the lag length, B is a vector of constants, and ε_t is the error term. The VAR model is used to forecast future values of the variables and to understand the impact of shocks to one variable on the others.

2.3. Random Forest (RF) Model

The Random Forest model is used for forecasting and prediction. This ensemble learning method combines multiple decision trees to improve accuracy and reduce overfitting. The Random Forest algorithm involves the following steps:

2.3.1. Build Multiple Decision Trees:

Each tree is constructed by selecting a random subset of features and data points. The prediction is based on aggregating the predictions of all the trees.

$$\text{Prediction} = (1 / T) \Sigma \text{Tree}_t(X)$$

where $\text{Tree}_t(X)$ is the prediction from the t-th decision tree, and T is the total number of trees.

The final forecast is obtained by averaging the predictions from all trees (regression) or taking a majority vote (classification).

$$\text{RF Forecast} = (1 / T) \Sigma \text{Tree}_t(X)$$

2.4. Dynamic Time Warping (DTW)

DTW is used to measure the similarity between two temporal sequences, which helps identify alignments between the price movements of Bitcoin and clean energy assets. The DTW distance between two time series X and Y is computed using the following formula:

$$D(i, j) = \text{dist}(X_i, Y_j) + \min(D(i-1, j), D(i, j-1), D(i-1, j-1))$$

where $\text{dist}(X_i, Y_j)$ is the distance between the i-th and j-th points of X and Y, respectively. The DTW distance helps in understanding the temporal alignment of Bitcoin's price changes with clean energy markets.

2.5. Analysis of Impulse Response Functions and Forecast Error Variance Decomposition

To understand the dynamic relationships between Bitcoin, gold, and clean energy assets, impulse response functions (IRFs) and forecast error variance decomposition (FEVD) are analyzed. IRFs show how a shock to one variable affects the other variables over time, while FEVD quantifies the proportion of the forecast error variance of each variable that is attributed to shocks from other variables.

$$IRF_{i,j}(h) = \Sigma A_{i,j,k} \varepsilon_{t-k}$$

where h represents the horizon of the forecast, and $A_{i,j,k}$ represents the impulse response of variable i to a shock in variable j.

FEVD_{i}(h) = Var(Forecast Error_{i, t+h}) / Total Variance

This decomposition helps to determine the extent to which shocks to Bitcoin influence the forecast errors of gold and clean energy returns.

This detailed methodology outlines the comprehensive approach used in this study to explore the impact of Bitcoin on gold and clean energy returns. By integrating traditional econometric models with advanced machine learning techniques, the study provides a robust framework for analyzing the complex interactions between these financial assets. The VAR model captures dynamic relationships, the Random Forest model offers advanced prediction capabilities, and the DTW technique provides insights into temporal alignments. Together, these methods address gaps in the literature and offer valuable insights for investors, policymakers, and academics.

3.0 Analysis and Results

3.1 Descriptive Statistics

Table 1 illustrates descriptive statistics of the study. The average price of Bitcoin stands at $20,363.56, reflecting its high valuation in the market. This figure, while substantial, is accompanied by a considerable standard deviation of $17,112.33, indicating pronounced volatility in Bitcoin prices over the observed period. This high level of fluctuation is further evidenced by the minimum and maximum values, which span from a low of $3,228.70 to a peak of $67,527.90, showcasing the extreme range of Bitcoin's market behavior.

When examining the quartiles, the 25th percentile (Q1) is at $7,511.25, the median (50th percentile) at $10,691, and the 75th percentile (Q3) at $33,809.40. This distribution reveals that the upper half of the data is notably more spread out, suggesting significant price increases in the higher range. The Shapiro-Wilk test result of 0.819986 indicates that Bitcoin prices deviate from a normal distribution. Additionally, the skewness value of 1.006396 confirms a positive skew, indicating a longer tail on the right side of the distribution, which means higher values are more frequent. The kurtosis value of -0.34611 suggests a flatter distribution compared to a normal distribution. The Jarque-Bera test statistic of 223.5026 further supports the non-normality of Bitcoin price data.

The average price of gold is $831.4521, with a standard deviation of $113.7686, showing less volatility compared to Bitcoin. Gold prices range from $622.25 to $1,056.83, indicating a more stable market. The 25th percentile is $705.605, the median is $874.03, and the 75th percentile is $919.7375, showing a relatively narrower interquartile range compared to Bitcoin. The Shapiro-Wilk test result of 0.916605 suggests that gold prices are closer to a normal distribution. The skewness value of -0.35168 indicates a slight negative skew, meaning there are more frequent lower values. The kurtosis value of -1.25421 suggests a flatter distribution than normal. The Jarque-Bera test statistic of 110.797 supports the non-normality of the distribution.

Green bonds have an average price of $101.7965 and a standard deviation of $8.385802, indicating relatively low volatility. The price ranges from $76.26968 to $113.9716. The quartiles show the 25th percentile at $100.4294, the median at $103.5276, and the 75th percentile at $107.1517, suggesting a narrow spread. The Shapiro-Wilk test result of 0.855824 indicates deviation from normality. The skewness value of -1.30771 shows a significant negative skew, indicating frequent lower values. The kurtosis value of 1.15365 suggests a distribution with lighter tails. The Jarque-Bera test statistic of 437.8465 confirms the non-normality of green bond prices.

Solar energy prices average $2,404.861 with a standard deviation of $1,225.4, indicating high volatility. Prices range from $815.6 to $4,812.6. The 25th percentile is $1,301.175, the median is $1,799.45, and the 75th percentile is $3,702.775, showing a wide spread in prices. The Shapiro-Wilk test result of 0.844273 suggests deviation from normality. The skewness value of 0.293306 indicates a slight positive skew. The kurtosis value of -1.629 shows a flatter distribution than normal. The Jarque-Bera test statistic of 160.63 confirms non-normality. Wind energy prices have an average of $2,653.079 and a standard deviation of $783.7347, indicating moderate volatility. Prices range from $1,609.2 to $5,174. The 25th percentile is $2,070.125, the median is $2,461.15, and the 75th percentile is $3,256.2. The Shapiro-Wilk test result of 0.918891 suggests closer adherence to normality. The skewness value of 0.777991 indicates a moderate positive skew. The kurtosis value of -0.30933 suggests a slightly flatter distribution. The Jarque-Bera test statistic of 134.8569 confirms non-normality.

BioCleanFuel prices average $1,111.815 with a standard deviation of $289.5319, showing moderate volatility. Prices range from $608.4 to $1,822.1. The 25th percentile is $884.55, the median is $1,006.95, and the 75th percentile is $1,262.05. The Shapiro-Wilk test result of 0.895459 indicates deviation from normality. The skewness value of 0.818288 shows a moderate positive skew. The kurtosis value of -0.50077 suggests a flatter distribution. The Jarque-Bera test statistic of 156.9536 confirms non-normality. Geothermal energy prices have an average of $1,215.796 and a standard deviation of $232.8379, indicating moderate volatility. Prices range from $825.4 to $2,144.26. The 25th percentile is $1,026.128, the median is $1,212.38, and the 75th percentile is $1,323.44. The Shapiro-Wilk test result of 0.936955 suggests closer adherence to normality. The skewness value of 0.954401 shows a positive skew. The kurtosis value of 1.266865 indicates a distribution with heavier tails. The Jarque-Bera test statistic of 281.2306 confirms non-normality. The VIX index has an average value of 21.24592 and a standard deviation of 8.258939, indicating significant volatility. The values range from 10.85 to 82.69. The 25th percentile is 15.835, the median is 19.705, and the 75th percentile is 24.655. The Shapiro-Wilk test result of 0.810276 indicates substantial deviation from normality. The skewness value of 2.50432 shows a strong positive skew. The kurtosis value of 11.11046 indicates a distribution with very heavy tails. The Jarque-Bera test statistic of 7958.664 confirms significant non-normality.

[Table 1 here]

Figure 1 shows correlation heatmap of the markets. The correlation matrix provides insights into the linear relationships between various market indices and Bitcoin, gold, green bonds, solar energy, wind energy, bioclean fuel, geothermal energy, and the VIX. The color scale ranges from blue (indicating negative correlations) to red (indicating positive correlations). Bitcoin shows a positive correlation with most of the other variables. It has a moderate positive correlation with gold (0.59) and significant positive correlations with solar energy (0.82), wind (0.65), bioclean fuel (0.83), and geothermal energy (0.56). These correlations suggest that as Bitcoin prices increase, the prices of these assets tend to increase as well. The correlation with VIX is very low (0.041), indicating little to no relationship with market volatility. Gold shows a moderate positive correlation with Bitcoin (0.59) and solar energy (0.77). It also has positive correlations with wind (0.61) and bioclean fuel (0.63). These relationships indicate that gold prices tend to move in the same direction as these assets. The correlation with VIX is moderate (0.41), suggesting a relationship with market volatility.

Green bonds show weaker correlations with the other variables. The highest positive correlation is with bioclean fuel (0.45) and geothermal energy (0.35). There is a weak negative correlation with solar energy (-0.19) and negligible correlations with Bitcoin, gold, wind, and VIX. This suggests that green bond prices do not significantly move in tandem with these assets. Solar energy shows strong positive correlations with Bitcoin (0.82) and gold (0.77). It also has positive correlations with wind (0.68) and bioclean fuel (0.76). The correlation with VIX is very low (0.083), indicating little to no relationship with market volatility. Wind energy prices have moderate to strong positive correlations with Bitcoin (0.65), gold (0.61), and solar energy (0.68). They also have positive correlations with bioclean fuel (0.82) and geothermal energy (0.59). The correlation with VIX is low (0.11), suggesting minimal relationship with market volatility.

BioCleanFuel shows significant positive correlations with Bitcoin (0.83), gold (0.63), solar energy (0.76), wind (0.82), and geothermal energy (0.56). These correlations indicate that bioclean fuel prices tend to move in the same direction as these assets. The correlation with VIX is slightly negative (-0.092), suggesting a minor inverse relationship with market volatility. Geothermal energy shows moderate positive correlations with Bitcoin (0.56), gold (0.63), solar energy (0.35), wind (0.59), and bioclean fuel (0.56). The correlation with VIX is low (0.14), indicating minimal relationship with market volatility. The VIX, which measures market volatility, shows low to negligible correlations with most variables. The highest correlation is with gold (0.41), indicating a moderate relationship with market volatility. Other correlations with Bitcoin, solar energy, wind, bioclean fuel, and geothermal energy are very low, suggesting that VIX does not significantly affect these assets.

[Figure 1 here]

The QQ plots in Figure 2 provide a visual representation of how the distribution of each asset compares to a normal distribution. Deviations from the red line (which represents the theoretical quantiles of a normal distribution) indicate departures from normality. The QQ plot for Bitcoin shows significant deviations from the normal distribution line, particularly at the tails. This indicates that Bitcoin prices are not normally distributed and exhibit heavy tails, which is consistent with the observed high volatility and extreme values in the data. The QQ plot for gold shows some deviations from the normal distribution line, particularly in the upper quantiles. While gold prices are closer to normality compared to Bitcoin, they still exhibit some skewness and kurtosis, indicating the presence of outliers and non-normal behavior in the distribution.

The QQ plot for green bonds shows deviations from the normal distribution line across the quantiles, especially in the lower and upper tails. This suggests that green bond prices do not follow a normal distribution and have significant skewness and kurtosis, reflecting the influence of outliers and non-standard behavior in the data. The QQ plot for solar energy displays notable deviations from the normal distribution line, particularly at the tails. This indicates that solar energy prices are not normally distributed, with significant skewness and kurtosis. The presence of heavy tails suggests higher probability of extreme values in solar energy prices. The QQ plot for wind energy shows some deviations from the normal distribution line, mainly at the tails. This suggests that wind energy prices have some level of skewness and kurtosis, indicating that they do not perfectly follow a normal distribution, but are closer compared to other assets like Bitcoin and solar energy. The QQ plot for bioclean fuel shows deviations from the normal distribution line, especially at the tails. This indicates that bioclean fuel prices are not normally distributed and exhibit significant skewness and kurtosis. The heavy tails suggest a higher likelihood of extreme values.

The QQ plot for geothermal energy shows notable deviations from the normal distribution line, particularly at the tails. This indicates that geothermal energy prices are not normally distributed and have significant skewness and kurtosis, reflecting the presence of outliers and non-normal behavior in the data. The QQ plot for the VIX shows significant deviations from the normal distribution line, especially in the upper quantiles. This indicates that the VIX, which measures market volatility, does not follow a normal distribution and exhibits heavy tails. The presence of extreme values is consistent with the nature of the VIX, which tends to spike during periods of high market volatility.

[Figure 2 here]

The time series plots in Figure 3 provide a visual representation of the price movements of Bitcoin, gold, green bonds, solar energy, wind energy, bioclean fuel, geothermal energy, and the VIX over the period from 2018 to 2023. Each plot reveals distinct trends and volatility characteristics for each asset.

The time series for Bitcoin shows significant volatility with pronounced peaks and troughs. From 2018 to early 2021, Bitcoin experienced relatively stable growth. However, starting in late 2020, Bitcoin's value surged dramatically, reaching a peak in late 2021 before experiencing a sharp decline in 2022. This volatility highlights Bitcoin's speculative nature and sensitivity to market conditions. Gold's time series indicates a steady increase in value from 2018 through mid-2020, likely driven by economic uncertainty and increased demand for safe-haven assets. Gold reached a peak in mid-2020, followed by some fluctuations, but remained relatively high compared to pre-2020 levels. The overall trend suggests that gold is less volatile than Bitcoin, but still subject to market influences.

The green bond time series shows a relatively stable value with minor fluctuations from 2018 to early 2021. However, there is a noticeable decline in late 2021 and early 2022. Despite this dip, green bonds generally exhibit lower volatility compared to other assets, reflecting their nature as a more stable investment tied to environmentally-focused projects. Solar energy prices show a steady increase from 2018 through late 2020, followed by a sharp rise in 2021, peaking in late 2021. This is followed by fluctuations, indicating increased interest and investment in solar energy during this period. The overall trend highlights significant growth in the solar energy sector, driven by technological advancements and increasing adoption of renewable energy sources.

The wind energy time series displays a steady growth pattern from 2018 to mid-2020, with a sharp increase in late 2020 and early 2021, similar to solar energy. After reaching a peak, wind energy prices experienced a decline in 2022 but remained higher than pre-2020 levels. This pattern reflects growing investments in renewable energy sources, with wind energy being a key component. The bioclean fuel time series shows notable volatility with significant peaks and troughs. From 2018 to early 2020, the prices were relatively stable, followed by a sharp rise in late 2020 and early 2021. However, prices declined in 2022, indicating the sector's susceptibility to market dynamics and changes in policy or technological advancements.

Geothermal energy prices exhibit moderate volatility with distinct peaks in early 2020 and mid-2021. Despite these fluctuations, the overall trend shows growth in the sector, reflecting increased investments and interest in geothermal energy as a reliable and sustainable energy source. The VIX time series, which measures market volatility, shows several spikes corresponding to periods of increased market uncertainty. Notably, there is a significant spike in early 2020, coinciding with the onset of the COVID-19 pandemic. The VIX remains relatively elevated compared to pre-2020 levels, indicating ongoing market volatility and uncertainty.

[Figure 3 here]

3.2 Impulse Response Function

Impulse response functions (IRFs) illustrate how shocks to one variable affect another variable over time. The plots in Figure 4 depict the responses of various financial and energy market variables to shocks in Bitcoin, gold, green bonds, solar energy, wind energy, and each other. A shock to Bitcoin itself shows a persistent positive response, gradually stabilizing over time. When gold experiences a shock, Bitcoin is negatively impacted initially, but then it adjusts and stabilizes. A shock to green bonds negatively affects Bitcoin initially, followed by a period of adjustment and stabilization. Similarly, a shock to solar energy causes an immediate increase in Bitcoin, which then stabilizes. Conversely, a shock to wind energy initially affects Bitcoin negatively, but the effect diminishes over time. In case of gold, a shock to Bitcoin has a minimal positive impact on gold, which stabilizes quickly. When gold experiences a shock itself, there is a persistent positive response with gradual stabilization. In contrast, a shock to green bonds has a slight negative impact on gold, which then stabilizes. A shock to solar energy positively impacts gold initially, followed by stabilization. Additionally, a shock to wind energy results in a slight positive impact on gold, which stabilizes over time. For green bonds, a shock to Bitcoin has a negligible impact on green bonds. Similarly, a shock to gold shows minimal effect on green bonds. When green bonds experience a shock themselves, there is a positive response with gradual stabilization. Conversely, a shock to solar energy negatively impacts green bonds initially, but the effect diminishes over time. A shock to wind energy has a minimal positive effect on green bonds.

Solar energy exhibits that a shock to Bitcoin has a minimal positive effect on solar energy, which stabilizes over time. When gold experiences a shock, there is a slight positive impact on solar energy. Conversely, a shock to green bonds negatively impacts solar energy initially, followed by stabilization. When solar energy experiences a shock itself, there is a positive response with gradual stabilization. A shock to wind energy positively impacts solar energy, which then stabilizes. Wind, on the other hand, showcase that a shock to Bitcoin has a minimal positive effect on wind energy, which stabilizes over time. When gold experiences a shock, there is a slight positive impact on wind energy. Similarly, a shock to green bonds has a minimal positive effect on wind energy. A shock to solar energy positively impacts wind energy, followed by stabilization. When wind energy experiences a shock itself, there is a positive response with gradual stabilization.

[Figure 4 here]

3.3 VAR Forecasts

Figure 5 presents the VAR forecasts for various markets, including Bitcoin, gold, green bonds, solar energy, wind energy, bioclean fuel, and geothermal energy. Each plot compares the actual values (in blue) with the forecasted values (in red) over a specified period. The Bitcoin forecast shows that the actual values frequently align with the forecasted values, although there are significant periods of deviation, especially during high volatility. The VAR model captures the general trend and some of the fluctuations, but the inherent volatility of Bitcoin presents challenges for accurate forecasting. This indicates that while the VAR model can provide some insights into Bitcoin price movements, its effectiveness is limited by the asset's high volatility.

The forecast for gold shows that the actual values closely follow the forecasted values. There are some deviations, especially during periods of volatility, but overall, the forecast model captures the trend and fluctuations reasonably well. This indicates that the VAR model is fairly effective in predicting gold prices, although there are occasional discrepancies. The forecast for green bonds displays a similar pattern, with actual values aligning closely with the forecasted values. While there are some periods where the actual values deviate from the forecasts, the overall trend is well captured by the model. The relatively stable nature of green bonds compared to other assets might contribute to the accuracy of the forecasts.

The solar energy forecast shows a higher degree of volatility in both actual and forecasted values. The model captures the general trend and some of the fluctuations, but there are notable periods where the actual values significantly deviate from the forecast. This suggests that while the VAR model can capture some aspects of solar energy price movements, it may struggle with the higher volatility and rapid changes in this market. The wind energy forecast demonstrates a pattern where the actual values frequently align with the forecasted values. Similar to solar energy, there are periods of volatility where the actual values deviate, but the overall trend is reasonably well captured. This indicates that the VAR model is somewhat effective in predicting wind energy prices, despite the inherent volatility in the market.

The forecast for bioclean fuel shows more significant deviations between actual and forecasted values compared to other assets. The model captures the general trend, but the actual values exhibit higher volatility, leading to frequent discrepancies. This suggests that the VAR model may have limitations in accurately predicting the prices of bioclean fuel, possibly due to market-specific factors and higher volatility. The geothermal energy forecast indicates that the actual values generally align with the forecasted values. There are some periods of divergence, but the overall trend is captured well by the model. This suggests that the VAR model is effective in predicting geothermal energy prices, which might be due to the relatively stable nature of this market compared to other clean energy sectors.

The VAR forecasts results show that the model performs well in predicting the prices of more stable assets like gold, green bonds, and geothermal energy, where actual and forecasted values closely align. This effectiveness is likely due to the relatively lower volatility and more predictable trends in these markets. In contrast, the forecasts for more volatile assets such as solar energy, wind energy, bioclean fuel, and Bitcoin exhibit greater discrepancies between actual and predicted values. This is because the higher volatility and rapid price changes in these markets make them more challenging to predict accurately using the VAR model. Thus, while the VAR model can capture general trends, its predictive power diminishes in the face of significant market volatility and instability.

[Figure 5 here]

3.4 Dynamic Time Warping (DTW) Technique

Figure 6 illustrates the Dynamic Time Warping (DTW) alignment results between Bitcoin and various assets, including gold, green bonds, solar energy, wind energy, bioclean fuel, and geothermal energy. The DTW technique measures the similarity between two temporal sequences by aligning them optimally, with the distance value indicating the degree of alignment. Lower distance values suggest a higher similarity between the sequences. The DTW alignment between Bitcoin and gold shows a distance of 32.57. The plot indicates some degree of synchronization, but the relatively higher distance value suggests that Bitcoin and gold prices do not closely follow each other. This is consistent with the differing market dynamics and factors influencing each asset.

The DTW alignment between Bitcoin and green bonds shows a distance of 36.44, indicating a weaker alignment compared to other assets. The plot reveals more significant deviations between the two sequences, suggesting that Bitcoin and green bonds exhibit less similar temporal patterns. This is expected given the distinct nature of cryptocurrencies and green bonds. The DTW alignment between Bitcoin and solar energy shows a distance of 29.07, the lowest among the assets analyzed. The plot indicates a relatively better alignment, suggesting that Bitcoin and solar energy prices have more similar temporal patterns. This could be attributed to overlapping market sentiments and external factors influencing both markets. The DTW alignment between Bitcoin and wind energy shows a distance of 30.24. The plot indicates a moderate alignment, with some synchronization between the two sequences. The similarity in temporal patterns might be influenced by common market trends and investor behavior affecting both Bitcoin and wind energy markets.

The DTW alignment between Bitcoin and bioclean fuel shows a distance of 29.93. The plot reveals a moderate degree of alignment, suggesting that the temporal patterns of Bitcoin and bioclean fuel prices exhibit some similarities. This could be due to shared market influences and investor sentiment affecting both assets. The DTW alignment between Bitcoin and geothermal energy shows a distance of 30.14. The plot indicates a moderate alignment, with some synchronization between the two sequences. The similarity in temporal patterns may be due to overlapping market factors and trends impacting both Bitcoin and geothermal energy prices.

The Dynamic Time Warping (DTW) results illustrate the degree of similarity between Bitcoin and other assets like gold, green bonds, solar energy, wind energy, bioclean fuel, and geothermal energy by measuring how closely their price movements align over time. A lower DTW distance indicates a higher degree of similarity in their temporal patterns, while a higher distance suggests less alignment. For example, Bitcoin and solar energy have the lowest DTW distance (29.07), indicating that their price movements are more synchronized compared to other assets. This similarity might be due to overlapping market sentiments or external factors affecting both markets, leading to more parallel trends in their price fluctuations.

On the other hand, Bitcoin and green bonds have the highest DTW distance (36.44), reflecting the least alignment between their price movements. This divergence can be attributed to the distinct nature of cryptocurrencies and green bonds, which are influenced by different market dynamics and investor behaviors. The moderate DTW distances for wind energy, bioclean fuel, and geothermal energy suggest some level of shared market influences with Bitcoin, but not as strong as with solar energy. Overall, the DTW analysis reveals that while there are varying degrees of similarity in the temporal patterns of Bitcoin and these assets, factors specific to each market play a significant role in shaping their price movements.

The economic significance of the DTW results lies in their ability to reveal the underlying relationships and potential co-movements between Bitcoin and various assets, providing valuable insights for investors and policymakers. By identifying which assets have more synchronized price movements with Bitcoin, market participants can better understand the interconnectedness and risk diversification opportunities within their portfolios. For instance, the strong alignment between Bitcoin and solar energy suggests that these markets might respond similarly to certain economic events or investor sentiments, indicating a potential for joint investment strategies or hedging. Conversely, the weak alignment with green bonds highlights the distinct nature of these markets, underscoring the importance of considering different economic factors when investing in or regulating these assets. Overall, DTW analysis helps in understanding the economic dynamics and interdependencies across different financial and energy markets, guiding more informed decision-making.

[Figure 6 here]

3.5 Random Forest Forecasts

Figure 7 shows random forest forecasts. The Random Forest (RF) prediction for gold shows that the model captures the general trend of actual returns, but there are notable deviations. The predicted values (in green) align closely with the actual values (in blue) most of the time, although during periods of higher volatility, the discrepancies become more evident. This suggests that while the RF model is effective in predicting gold returns, it struggles with capturing extreme movements accurately.

For green bonds, the RF predictions also show a general alignment with actual returns, but with occasional deviations. The predicted values track the actual returns closely during periods of lower volatility, but during spikes or drops, the model's predictions are less accurate. This indicates that the RF model can provide reasonable forecasts for green bond returns, but its performance diminishes during more volatile periods. The prediction for solar energy returns reveals that the RF model captures the overall pattern of the actual returns fairly well. However, similar to gold and green bonds, there are discrepancies during periods of significant volatility. The RF model's predictions are generally accurate, but it tends to underestimate or overestimate returns during sudden market movements, reflecting the challenges in forecasting highly volatile assets.

The RF prediction for wind energy returns demonstrates a reasonable alignment with the actual returns. The model follows the trend of the actual values closely, but there are periods where the predictions deviate, especially during sharp increases or decreases in returns. This suggests that while the RF model is competent in forecasting wind energy returns, it may not fully capture the extent of rapid market changes. For bioclean fuel, the RF predictions show a good fit with the actual returns, particularly during periods of lower volatility. However, as with other assets, the model's accuracy decreases during extreme market movements. The RF model generally captures the trends in bioclean fuel returns, but its predictive power is limited when faced with abrupt changes in the market. The RF prediction for geothermal energy returns indicates that the model aligns well with the actual returns in most cases. The predicted values match the actual returns closely, but the model struggles during periods of high volatility, leading to occasional large discrepancies. This pattern suggests that the RF model is effective in predicting geothermal energy returns under stable market conditions, but less so during volatile periods.

The Random Forest (RF) predictions for various assets, including gold, green bonds, solar energy, wind energy, bioclean fuel, and geothermal energy, generally align well with the actual returns, capturing the overall trends and patterns. The predicted values closely follow the actual values during periods of market stability, demonstrating the RF model's capability to forecast returns effectively under normal conditions. However, during periods of significant volatility, the predictions tend to deviate more from the actual returns, indicating that the model struggles to accurately capture sudden and extreme market movements. This pattern of performance highlights both the strengths and limitations of the RF model in financial forecasting. While it is a robust tool for predicting returns in relatively stable markets, its predictive power diminishes in the face of abrupt changes and high volatility. This suggests that investors and analysts can rely on RF models for general trend analysis and forecasting under typical market conditions but should be cautious and consider additional models or methods when dealing with highly volatile assets or periods of significant market upheaval.

The economic significance of the Random Forest (RF) predictions lies in their ability to provide investors and policymakers with valuable insights into market trends and potential future returns. By accurately forecasting returns during stable periods, RF models can aid in strategic decision-making, helping investors optimize their portfolios and manage risks effectively. For assets like gold, green bonds, and clean energy sectors, reliable predictions can enhance investment strategies, promote more informed trading decisions, and support the allocation of resources towards more stable and predictable investments. However, the limitations of the RF model during periods of high volatility underscore the need for caution. During market turbulence, the model's reduced accuracy can lead to misguided investment decisions if relied upon exclusively. Understanding these limitations is crucial for investors, as it highlights the importance of complementing RF predictions with other analytical tools and models that can better account for sudden market shifts. This balanced approach can improve risk management and help in navigating volatile markets more effectively, ultimately contributing to more resilient investment portfolios and economic stability.

[Figure 7 here]

3.6 Cross-Correlations

The cross-correlation plots in Figure 8 illustrate the relationship between Bitcoin and various assets (gold, green bonds, solar energy, wind energy, bioclean fuel, and geothermal energy) over different time lags. Positive values indicate that an increase in Bitcoin is associated with an increase in the other asset, while negative values indicate an inverse relationship. The time lags on the x-axis show how past values of one asset correlate with future values of another. The cross-correlation between Bitcoin and gold shows generally low correlations at various lags, both positive and negative. There are periods where the correlation is slightly positive or negative, but overall, the relationship is weak. This suggests that the price movements of Bitcoin and gold are relatively independent of each other, with no strong leading or lagging relationship.

The cross-correlation plot for Bitcoin and green bonds indicates low to moderate correlations at different lags. There are occasional peaks where the correlation is slightly positive, suggesting some periods where Bitcoin and green bonds may move together. However, these correlations are generally weak, indicating limited interaction between the two assets over time. The cross-correlation between Bitcoin and solar energy shows more variability, with alternating periods of positive and negative correlations. Some lags exhibit moderate correlations, suggesting that there are times when the price movements of Bitcoin and solar energy are somewhat related. However, the overall pattern indicates a complex and inconsistent relationship between these two markets.

The cross-correlation plot for Bitcoin and wind energy displays similar characteristics to the solar energy plot, with alternating periods of positive and negative correlations. There are some lags where moderate correlations are observed, indicating occasional alignment in their price movements. Nonetheless, the overall relationship remains weak and inconsistent. The cross-correlation between Bitcoin and bioclean fuel shows generally low correlations across different lags. There are brief periods of moderate positive correlation, suggesting some transient interactions between their price movements. However, the overall weak correlation indicates that Bitcoin and bioclean fuel prices largely move independently. The cross-correlation plot for Bitcoin and geothermal energy exhibits low to moderate correlations at various lags, with some peaks indicating transient periods of positive correlation. These occasional correlations suggest that there might be specific times when the price movements of Bitcoin and geothermal energy are aligned. However, the overall relationship is not strong or consistent.

The cross-correlation analysis reveals that Bitcoin's price movements have weak and inconsistent relationships with gold, green bonds, solar energy, wind energy, bioclean fuel, and geothermal energy. This means that changes in Bitcoin's price do not strongly predict or follow the price changes in these other assets. For instance, while there are brief periods where Bitcoin and these assets might move together, these correlations are generally low and fluctuate between positive and negative values. This suggests that the price dynamics of Bitcoin are largely driven by factors unique to its market, and it doesn't have a stable, predictable impact on, or response to, the price movements of these other assets. In practical terms, investors cannot rely on Bitcoin's price trends to consistently forecast the behavior of these other markets, highlighting the distinct nature and drivers of each asset class.

The economic significance of the cross-correlation analysis lies in its implications for diversification and risk management in investment portfolios. The generally weak and inconsistent correlations between Bitcoin and other assets like gold, green bonds, solar energy, wind energy, bioclean fuel, and geothermal energy suggest that Bitcoin can serve as a diversifying asset. Because Bitcoin's price movements are largely independent of these other assets, including it in a portfolio could help spread risk and reduce the overall volatility. For policymakers and market analysts, these findings highlight the distinct market dynamics that drive Bitcoin compared to more traditional and renewable energy assets. This independence implies that shocks or trends in the Bitcoin market are unlikely to have a significant ripple effect on these other markets. Consequently, regulatory policies and economic forecasts for Bitcoin can be developed with an understanding that Bitcoin operates under a different set of influences than other financial and energy markets. This separation helps in creating more targeted and effective policies tailored to the unique characteristics of each market.

[Figure 8 here]

4.0 Conclusion

The advanced machine learning analysis reveals that Bitcoin exhibits high volatility and distinct market behavior compared to gold and clean energy assets. While Bitcoin shows moderate correlations with solar and wind energy, indicating some interconnectedness driven by broader market trends, its overall relationship with gold and green bonds is weak. Impulse response functions and cross-correlation analyses highlight that Bitcoin's price movements are largely independent, making it a potentially effective diversifying asset. However, forecasting Bitcoin's returns remains challenging due to its volatility, as evidenced by the limitations of VAR and RF models during periods of market instability.

Dynamic Time Warping (DTW) results show that Bitcoin has the closest alignment with solar energy, indicating similar temporal patterns. However, the alignment with green bonds is weak, reflecting distinct market dynamics. Cross-correlation analysis indicates weak and inconsistent relationships between Bitcoin and other assets, implying that Bitcoin's price movements are largely independent of these markets.

Bitcoin's impact on gold and clean energy returns, as analyzed through advanced machine learning techniques, demonstrates both its potential for influence and its distinct behavior compared to traditional and renewable energy assets. The high volatility and unique market dynamics of Bitcoin suggest that while it shares some interconnectedness with clean energy markets, particularly solar and wind energy, its overall impact remains complex and multifaceted. Economically, the weak and inconsistent correlations between Bitcoin and other assets indicate that Bitcoin can serve as a diversifying asset in investment portfolios. Its relative independence from traditional and renewable energy markets helps spread risk and reduce overall portfolio volatility. For policymakers, these findings highlight the necessity of tailored regulatory policies that address the unique characteristics of Bitcoin and other distinct asset classes.

The study carries significant implications for practitioners and policymakers. For policymakers, the findings underscore the necessity of developing tailored regulatory frameworks that address the unique characteristics of Bitcoin and its impact on financial markets. Given Bitcoin's high volatility and its distinct market behavior, regulations should focus on mitigating systemic risks while promoting transparency and investor protection. Policies should also consider the potential for Bitcoin to serve as a diversifying asset, encouraging innovation in financial products that incorporate cryptocurrencies responsibly. Additionally, understanding the nuanced relationships between Bitcoin and clean energy markets can help in crafting policies that support sustainable investment practices.

Financial practitioners, including fund managers and analysts, should leverage the insights from this analysis to enhance their investment strategies. The moderate correlations between Bitcoin and renewable energy assets like solar and wind energy suggest potential for diversified portfolio construction. Practitioners should employ advanced machine learning techniques to improve their forecasting models, acknowledging the limitations identified in this study, especially during volatile market conditions. Integrating Bitcoin into investment portfolios requires a balanced approach that considers its high volatility and independent market movements to optimize returns while managing risks.

For investors, the study highlights both the opportunities and challenges associated with incorporating Bitcoin into their investment portfolios. Bitcoin's potential as a diversifying asset can help reduce overall portfolio volatility, especially when combined with more stable assets like gold and green bonds. However, investors must be mindful of Bitcoin's high volatility and the difficulties in accurately forecasting its returns. A diversified investment approach, informed by advanced analytics and a thorough understanding of market dynamics, can help mitigate risks and capitalize on Bitcoin's potential benefits. The broader financial markets can benefit from the insights provided by this analysis by recognizing the interconnectedness and unique behaviors of Bitcoin compared to traditional and renewable energy assets. The weak and inconsistent correlations between Bitcoin and other assets highlight the importance of maintaining diverse and resilient market structures. Financial markets should continue to innovate in creating products and services that leverage the strengths of cryptocurrencies while addressing their inherent risks. Understanding Bitcoin's impact and predictability can lead to more informed market practices, fostering stability and growth in an increasingly complex financial ecosystem.

The findings from this study present significant implications for the academic community, particularly in the fields of finance, economics, and sustainable development. The complex relationships and unique behaviors of Bitcoin compared to traditional and renewable energy assets provide a fertile ground for further theoretical exploration and empirical investigation. This study underscores the necessity for developing robust models that can better capture the volatility and dynamics of cryptocurrencies, which traditional financial theories may not fully address. For research scholars, the study highlights several avenues for future research. The moderate correlations between Bitcoin and renewable energy assets, such as solar and wind energy, suggest potential interdisciplinary studies examining the intersection of cryptocurrency markets and sustainable investments. Scholars can build on these findings to explore the causative factors behind these correlations and their implications for market behavior. Additionally, the challenges identified in forecasting Bitcoin’s returns using VAR and RF models point to the need for developing and testing more sophisticated machine learning algorithms and hybrid models that can handle high volatility and market instability more effectively.

Academia can leverage these findings to enhance curriculum development and educational programs in finance and economics. Incorporating the study of cryptocurrencies and their impact on traditional and clean energy markets into academic courses can prepare students for the evolving financial landscape. This includes teaching advanced machine learning techniques and their applications in financial forecasting, as well as emphasizing the importance of risk management in dealing with volatile assets like Bitcoin. Furthermore, academic institutions can foster collaborative research initiatives that bring together experts in finance, technology, and sustainability to explore the multifaceted impacts of cryptocurrencies on global markets.

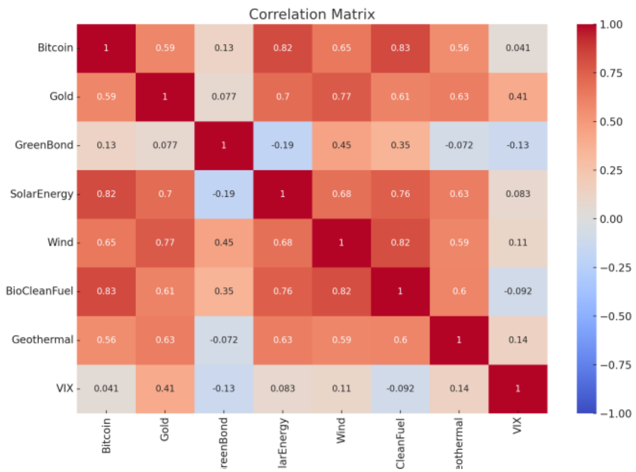
This study has several limitations that should be acknowledged. Firstly, the high volatility of Bitcoin and its unique market dynamics pose challenges in achieving accurate and reliable forecasts, as evidenced by the performance of the VAR and RF models. These models, while advanced, may not fully capture the complex behavior and rapid market changes characteristic of cryptocurrencies. Additionally, the data used in this study may be subject to temporal biases, and the period analyzed may not encompass all possible market conditions, potentially limiting the generalizability of the findings. Furthermore, the study focuses on a limited number of assets, which may not provide a comprehensive view of Bitcoin's impact on the broader financial market and other asset classes.

Future research should aim to address these limitations by exploring more sophisticated and hybrid modeling techniques that can better handle the volatility and unpredictability of cryptocurrency markets. Researchers can also expand the scope of the study to include a wider range of assets and longer time periods to enhance the robustness and applicability of the findings. Investigating the causative factors behind the correlations between Bitcoin and renewable energy assets can provide deeper insights into market behavior. Additionally, interdisciplinary studies that integrate financial analysis with technological and environmental considerations can offer a more holistic understanding of Bitcoin's impact on global markets. Exploring the regulatory implications and developing frameworks that can effectively manage the risks and opportunities associated with cryptocurrencies is another valuable avenue for future research.

Table 1: Descriptive Statistics

	Mean	Std.	Min	25%	50%	75%	Max	Shapiro-Wilk Test	Skewness	Kurtosis	Jarque-Bera Test
Bitcoin	20363.56	17112.33	3228.7	7511.25	10691	33809.4	67527.9	0.819986	1.006396	-0.34611	223.5026
Gold	831.4521	113.7686	622.25	705.605	874.03	919.7375	1056.83	0.916605	-0.35168	-1.25421	110.797
GreenBond	101.7965	8.385802	76.26968	100.4294	103.5276	107.1517	113.9716	0.855824	-1.30771	1.15365	437.8465
SolarEnergy	2404.861	1225.4	815.6	1301.175	1799.45	3702.775	4812.6	0.844273	0.293306	-1.629	160.63
Wind	2653.079	783.7347	1609.2	2070.125	2461.15	3256.2	5174	0.918891	0.777991	-0.30933	134.8569
BioCleanFuel	1111.815	289.5319	608.4	884.55	1006.95	1262.05	1822.1	0.895459	0.818288	-0.50077	156.9536
Geothermal	1215.796	232.8379	825.4	1026.128	1212.38	1323.44	2144.26	0.936955	0.954401	1.266865	281.2306
VIX	21.24592	8.258939	10.85	15.835	19.705	24.655	82.69	0.810276	2.50432	11.11046	7958.664

Figure 1: Heatmap of Markets



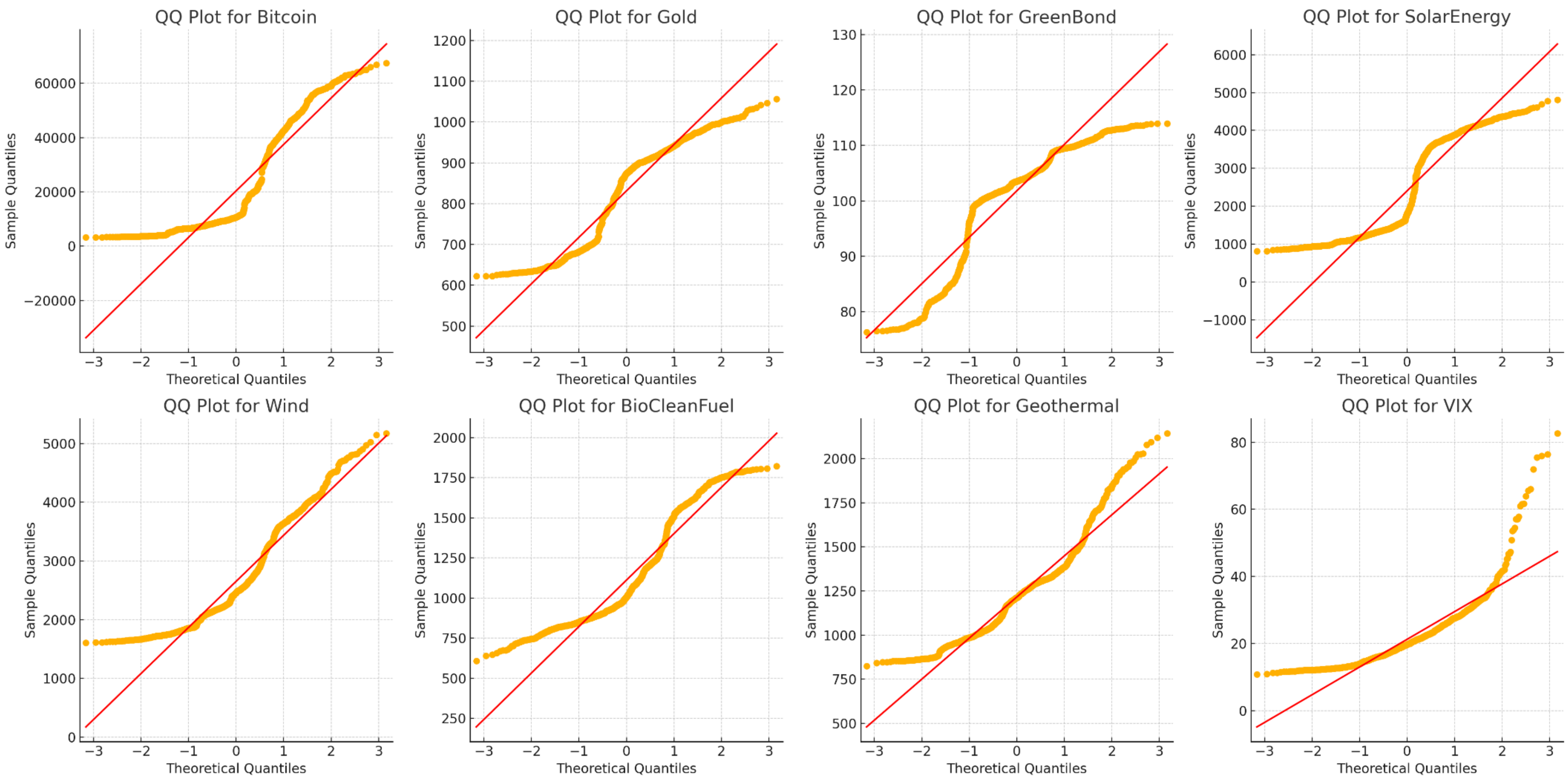


Figure 2: Q-Q Plots of Bitcoin, Gold, and Clean Energy Markets

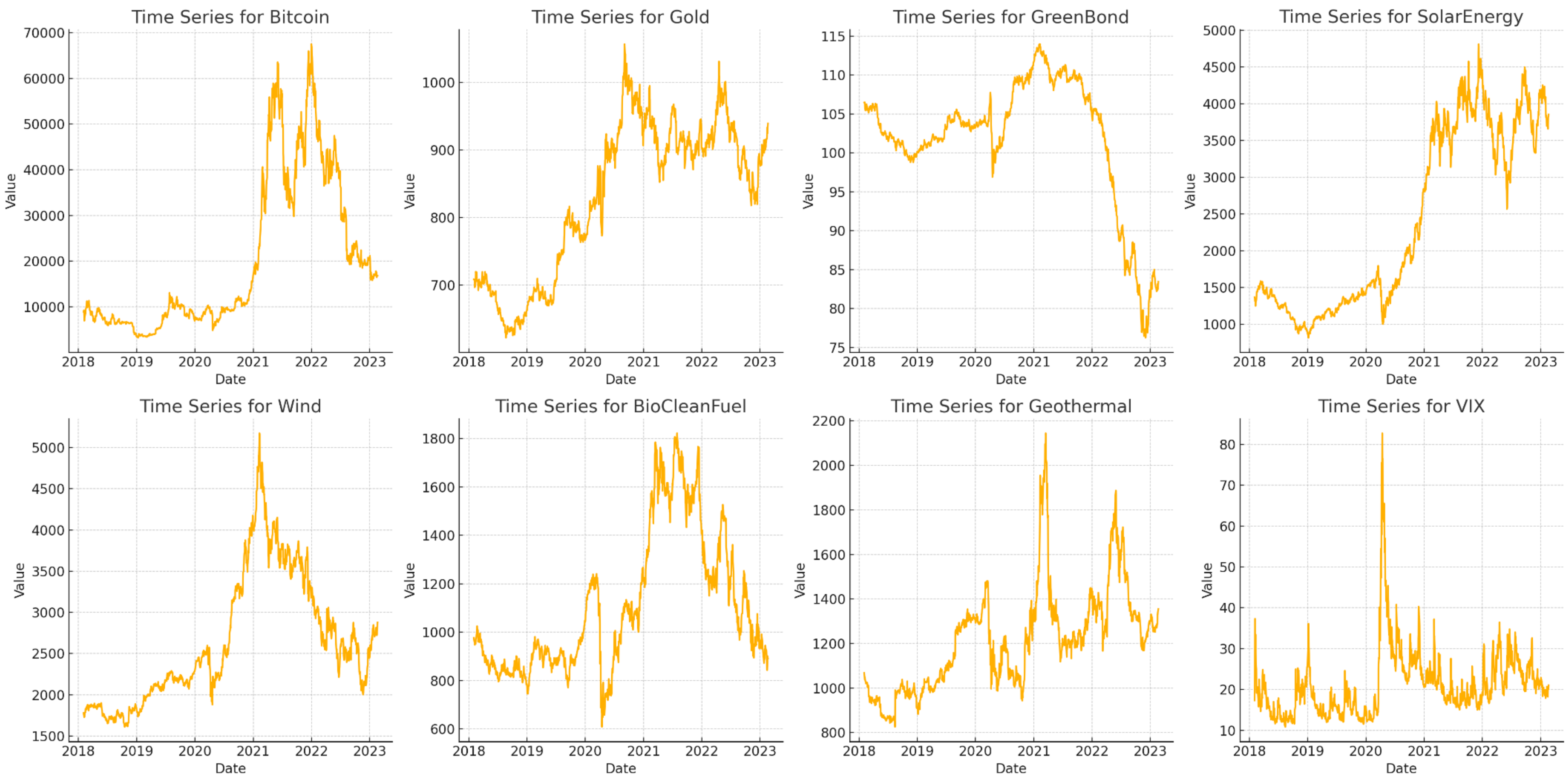


Figure 3: Time Series Plots of Bitcoin, Gold, and Clean Energy Markets

Figure 4: Impulse Response Function of Bitcoin, Gold and Clean Energy Markets

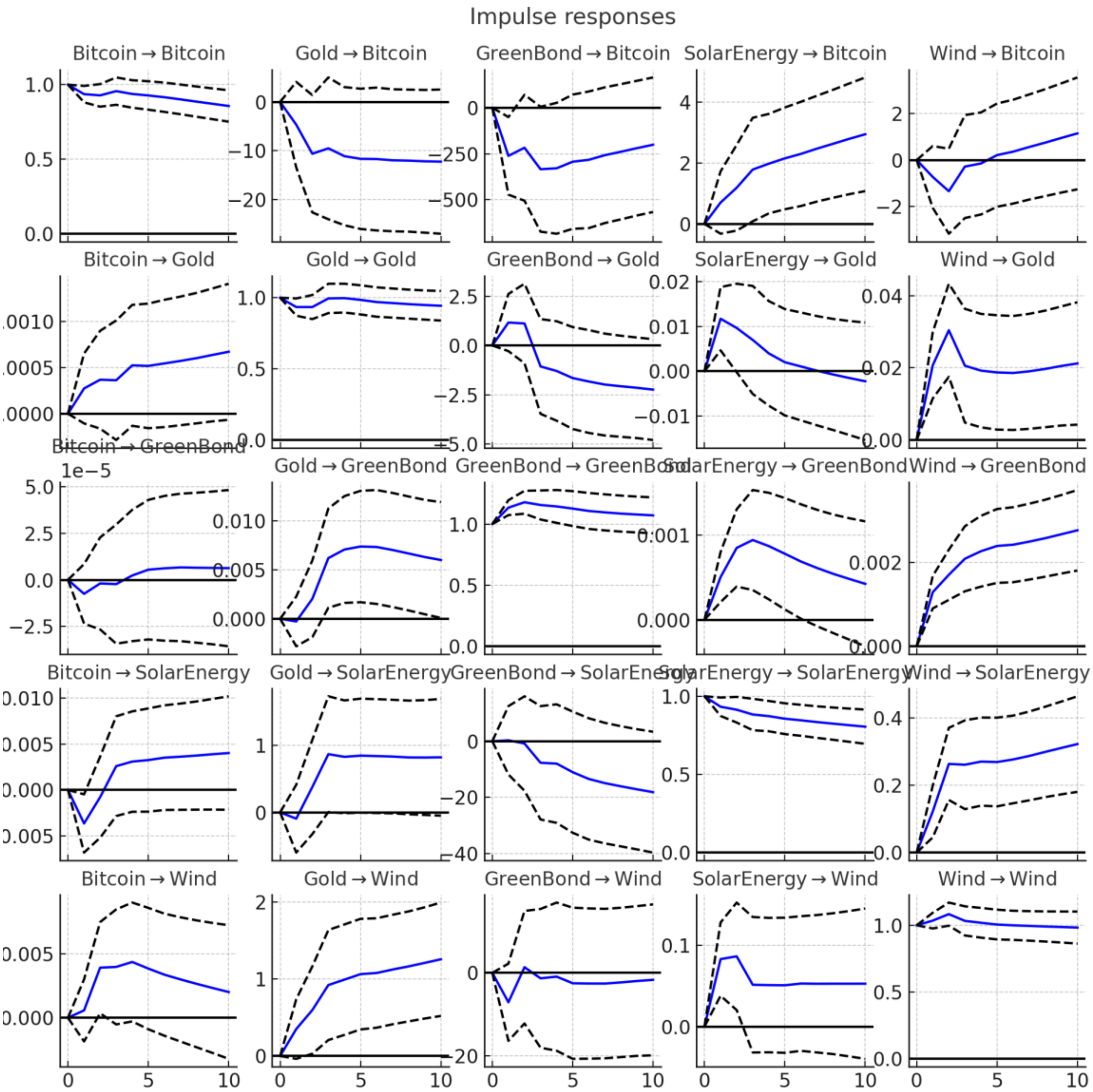


Figure 5: Vector Autoregression Forecasts for Bitcoin, Gold and Clean Energy Markets

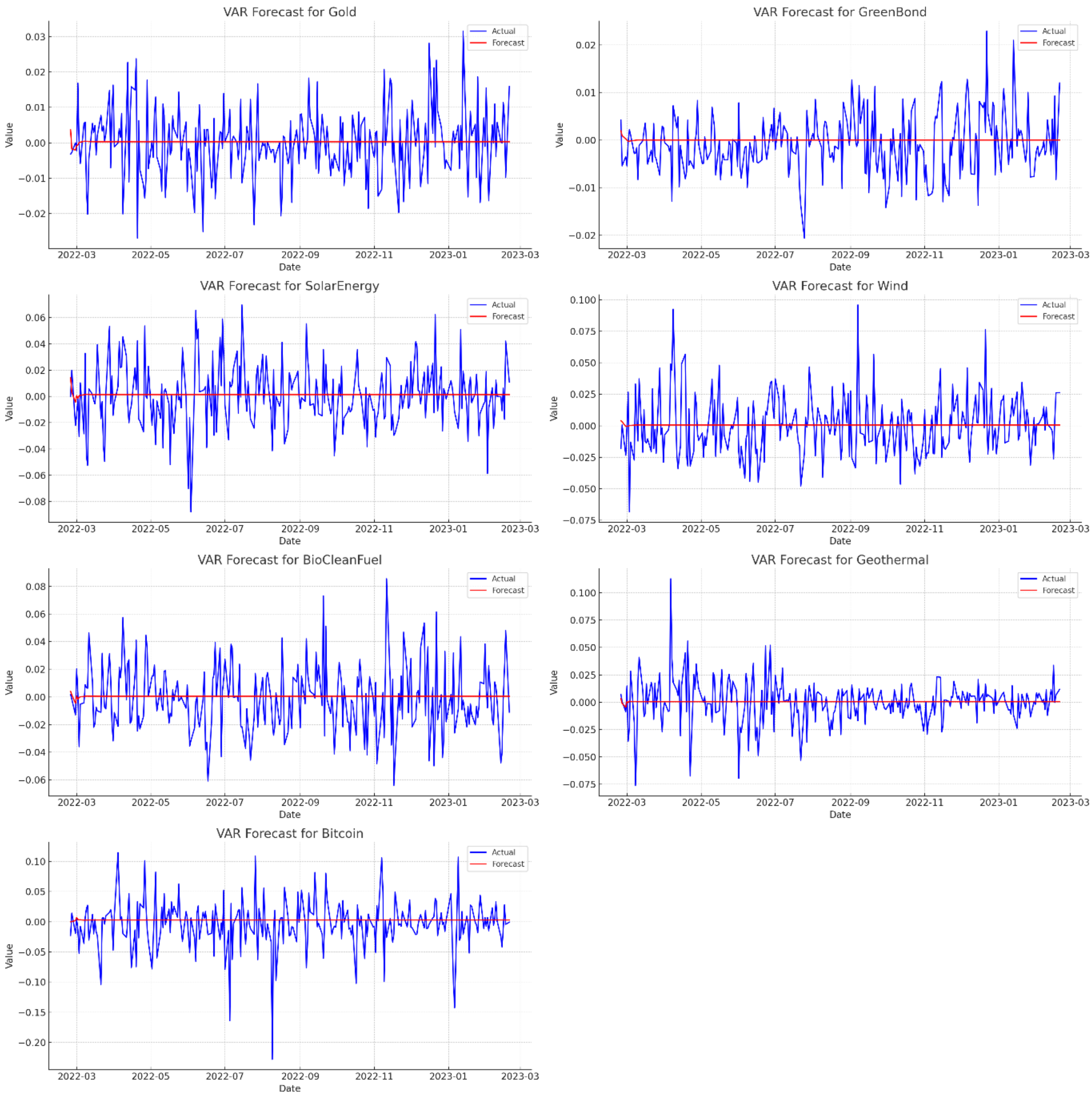


Figure 6: Machine Learning Technique Dynamic Time Warping (DTW) Results

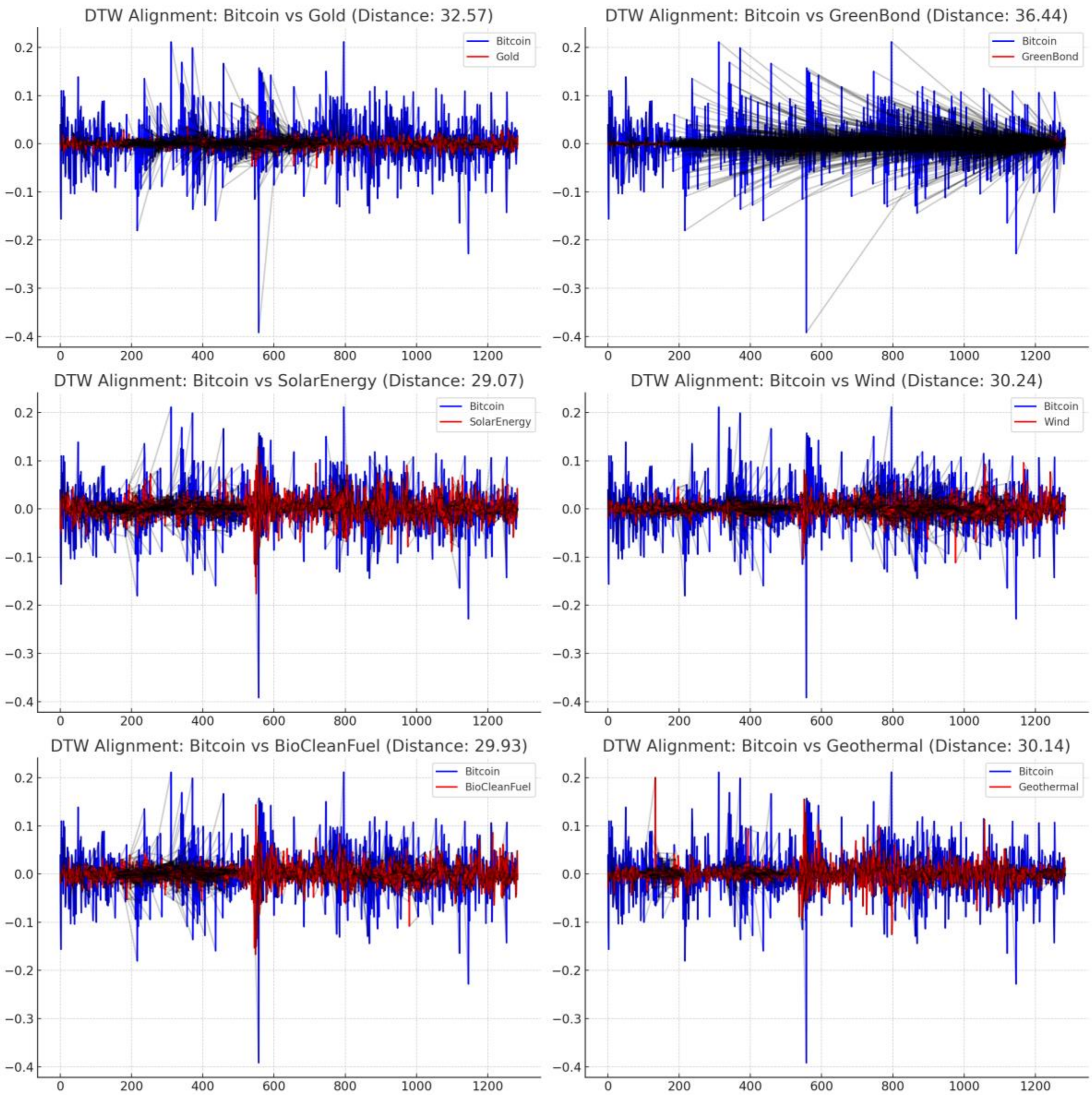


Figure 7: Machine Learning based Predictions (Random Forest Comparisons)

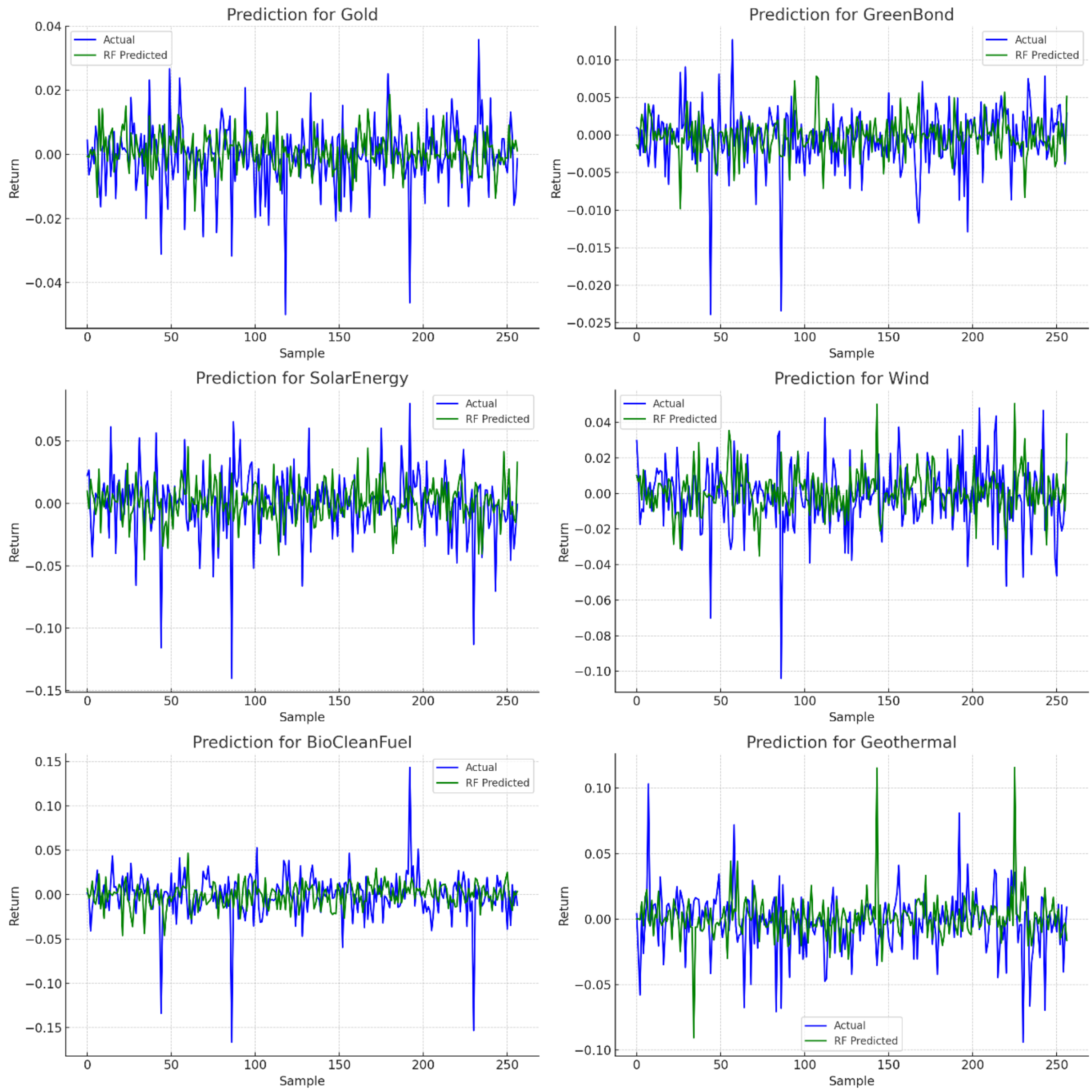


Figure 8: Cross-Correlations