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Title of research article

Examining the hedge and safe-haven abilities of Green financial assets

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Abstract
Green assets have garnered substantial attention from issuers, investors, and governments, being regarded as distinctive instruments aligned with sustainability objectives and compatible with a low-carbon economy. They have also emerged as potential tools for hedging against the risks of other assets. Accordingly, this study investigates whether green assets serve as effective hedges against financial asset volatility and whether they provide safe-haven properties during periods of geopolitical tensions (GPR) and climate policy uncertainty (CPU). The analysis employs daily and monthly data spanning the period 2014–2025, utilizing the MIDAS-DCC model. The findings reveal that green bonds and green cryptocurrencies acted as safe havens against equity investment risks. Moreover, the results indicate that GPR and CPU influence asset correlations in distinct ways. Both green bonds and green cryptocurrencies demonstrate safe-haven characteristics when GPR and CPU reach elevated levels. These results provide important details about the interactions among the study variables and underscore the need for future research to examine additional determinants in order to achieve a more comprehensive understanding of investment trends in green assets.
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1. Introduction:

In response to the international community's mounting concerns regarding climate change, regulatory authorities across the world have introduced a range of environmental policies designed to curb carbon dioxide emissions, mitigate the pace of climate deterioration, and safeguard the planet, thereby promoting sustainable development. Within this framework, the significance of adopting national strategies and programs to facilitate the gradual transition toward environmentally friendly products has become increasingly evident. Such an objective is achieved by redirecting capital markets toward green financing instruments, in alignment with the Sustainable Development Goals, which has consequently fostered the expansion of greener (Zhang, Zhang, & Managi, 2019), cleaner, and more socially responsible financial markets. Green cryptocurrencies, alongside the green bonds first issued by the

European Investment Bank in 2007, represent among the most innovative instruments for financing low-carbon projects. These instruments are designed to foster the development of renewable energy and enhance resource-use efficiency. Over the past years, this market has experienced rapid expansion and has attracted growing attention from financial market participants, investors, and policymakers alike (Initiative, 2023).

The evolution of green financial markets has rendered green assets increasingly eligible as portfolio diversification instruments. Consequently, the volatility of their prices, their dynamic interactions with other asset classes, and their indirect effects have attracted significant attention within academic circles. A growing body of literature suggests that green assets can serve as diversification tools for traditional instruments, with the potential to hedge against risks associated with other assets, particularly under conditions of heightened market volatility, recurrent geopolitical events, and rising policy uncertainty (Kılıç & Altan, 2023) (Yadav, Mishra, & Ashok, 2023) (Yousaf, Suleman, & Demirer, 2022). Conversely, other studies argue that despite the global recognition of their importance, the financial performance of green assets—specifically their ability to act as a safe haven or hedge—remains insufficiently assessed both under normal market conditions and during episodes of market turmoil. This debate raises critical questions regarding the existence of dynamic conditional linkages between green assets and conventional financial assets over the period 2014–2025 and whether green assets can indeed serve as a safe haven amid geopolitical tensions, economic uncertainty, and climate-related risks.

Recently, academic interest in green assets and their role in enhancing financial stability has grown significantly. However, the existing literature remains limited in analyzing the extent to which these assets integrate with traditional financial instruments, particularly under conditions of geopolitical risk and policy uncertainty. For instance, (Kuang, 2025) examined the role of green cryptocurrencies in improving portfolio resilience and found that such assets help mitigate tail risks during periods of market stress, thereby enhancing portfolio stability. Nevertheless, they do not yield higher returns or outperform traditional assets, a finding that partially aligns with (Kılıç & Altan, 2023), who identified green cryptocurrencies as among the relatively safest digital investment options for investors. However, the scope of these studies remains constrained, as they are limited to short time horizons and focus exclusively on the cryptocurrency market, which restricts the generalizability of their findings to other categories of green assets.

In a similar vein, (Pham & Nguyen, 2021) examined the relative dependence between green bonds and other asset classes—including energy markets, equities, and traditional bonds—across U.S. and European markets. Their findings revealed that the hedging benefits of green bonds vary across market conditions, with correlations fluctuating significantly between periods of turbulence and stability. Likewise, (Kocaarslan, 2021) confirmed the presence of a time-varying dynamic relationship between green and conventional bond markets, demonstrating that both asset types provide diversification opportunities during times of crisis. Moreover, the study indicated that an appreciation of the U.S. dollar enhances conditional correlations between these markets, thereby contributing to a reduction in the cost of capital associated with green bonds. However, the temporal constraints of these findings prevent them from adequately accounting for broader macroeconomic risks.

On the other hand, (Haq, Chupradit, & Huo, 2021) demonstrated that green bonds function more as a hedging instrument than as a safe haven against economic policy uncertainty in both China and the United Kingdom. Moreover, their findings indicated that green bonds complement clean energy stocks, particularly during the COVID-19 pandemic, which enhances portfolio diversification. Similarly, (Hung, 2021) found that the relationship between green bonds and traditional assets—such as Bitcoin, the S&P 500 index, and the clean energy index—is asymmetric, revealing the capacity of green bonds to provide protection against price volatility in financial markets, especially during periods of turbulence. In line with these results, (Naeem, Adekoya, & Oliyide, 2021) identified strong long-term correlations between green bonds and assets such as crude oil, gold, and silver, noting that positive return effects tend to be short-lived, whereas negative return impacts persist longer, underscoring the asymmetric nature of these interactions over different time horizons.

More recent studies, such as (Dong, Xiong, & et al, 2023) and (Zhang, Hong, & Ding, 2023), advanced the analysis to a higher level of complexity by incorporating geopolitical risk (GPR) and climate policy uncertainty (CPU) as explanatory variables. Their findings revealed that these factors introduce heterogeneity in the nature of correlations between green and conventional assets, with the magnitude and direction of the effects varying according to the source of risk. Specifically, while climate policy uncertainty (CPU) tends to strengthen the role of green bonds as a safe haven, geopolitical risks (GPR) appear to increase risk co-movements across asset classes, thereby reducing diversification benefits. These conclusions are further supported by (Ding, Ji, & et al, 2022), who found that rising levels of policy uncertainty (CPU) weaken the hedging relationship between high- and low-carbon assets, reflecting the fragility of cross-asset linkages amid environmental policy instability.

Similarly, (Imran & Ahad, 2023) and (Yadav, Mishra, & Ashok, 2023) provided quantitative evidence using advanced econometric frameworks such as the Cross-Quantilogram and Diebold & Yilmaz (2012) models, demonstrating that green assets—particularly green bonds—serve as effective short-term diversification instruments, although their impact tends to diminish over the long run. These findings align with those of (Haq, Maneengam, & et al, 2023), who showed that digital green bonds exhibit wavelet-based co-movement with non-green cryptocurrencies, highlighting an emerging dynamic interdependence between traditional and digital asset classes within the evolving landscape of sustainable finance.

Within the context of financial crises, (Yousaf, Suleman, & Demirer, 2022) found that green bonds were the only asset class that maintained their safe-haven property during the COVID-19 pandemic, a finding partially supported by (Ren, Lucey, & Luo, 2023), who noted a gradual erosion of this characteristic in the post-crisis period. Finally, (Rehan, Mohti, & Ferreira, 2024) revealed that periods of geopolitical turmoil—such as the Russia–Ukraine war—intensify the interconnectedness between green and conventional assets, positioning green instruments as central conduits for risk transmission across global financial markets.

Based on the reviewed literature, what distinguishes the present study is its focus on examining the role of green assets in financial markets during a recent period characterized by heightened volatility and intensified economic, political, and climate-related uncertainties. Specifically, this study investigates the relationship between green and traditional financial assets and evaluates the impact of geopolitical risks and climate policy uncertainty on their interactions. Accordingly, the research aims to assess whether green assets function as effective hedging instruments or safe-haven assets against traditional financial instruments under conditions of global instability.

2. Methodology:

Investors often seek to protect their assets through portfolio diversification or by employing hedging instruments, particularly during periods of financial market uncertainty triggered by crises. An asset that exhibits a weak average correlation with the underlying asset is referred to as a diversifier, with diversification aiming to mitigate idiosyncratic risks associated with financial market investments. The rationale behind diversification is that the positive performance of certain assets may offset the negative performance of others within the portfolio, provided that the assets are not perfectly correlated. A hedge, by contrast, refers to an asset that is typically uncorrelated or negatively correlated with the underlying asset on average. Moreover, an asset that demonstrates negative correlation with the primary asset during periods of economic downturn is commonly referred to as a safe haven (Ren, Lucey, & Luo, 2023). In other words, a safe haven is an investment that is expected to preserve, or even increase, its value when financial markets are exposed to negative shocks. The presence of such assets within an investment portfolio allows investors to offset potential losses under adverse market conditions, as well as during periods of financial turmoil and crises (Baur & Lucey, 2010).

The study relies on daily data for the S&P Green Bond Index and the green cryptocurrency XRP, which are employed as proxies for green financial assets and obtained from Bloomberg. In addition, daily data were collected for major stock market indices, namely the S&P 500 and the Dow Jones Industrial Average (DJI100). The analysis also incorporates daily data on key global commodities—crude oil and gold—as well as Bitcoin, all sourced from Bloomberg. With respect to uncertainty measures, monthly data were used for the Geopolitical Risk Index, obtained from the Matteo Iacoviello database, and the Global Climate Policy Uncertainty Index, sourced from policyuncertainty.com. The study focuses on the period from January 1, 2014, to July 1, 2025, which was selected both for its distinctive characteristics of heightened volatility and uncertainty and for the availability of consistent data.

In order to achieve the objectives of this study, the DCC-GARCH model was employed to measure the dynamic conditional correlations among the variables under investigation. Furthermore, the DCC-MIDAS model was applied to examine the impact of geopolitical risks and climate policy uncertainty on the dynamic correlations of the study variables.

2.1. DCC-GARCH:

The DCC-GARCH model, developed by Engle (2002), was designed to capture potential changes in conditional correlations over time. This model assumes that the time series follows a normal distribution with a zero mean and a conditional variance H_t. The estimation procedure is carried out in two steps: first, the univariate GARCH model is estimated; subsequently, the conditional correlations are derived as follows (Naas, Bensania, & Bendob, 2019, p. 17):

$$r_t = \mu_t + \varepsilon_t \quad \frac{\varepsilon_t}{\Omega_{t-1}} \to N(0, H_t)$$

$$H_t = D_t R_t D_t$$

Where:

r_t is the matrix of rank (1 × K);

ε_t is the residuals and represents a matrix of rank (1 × K);

Ω_{t-1} is an array of all information available up to date t;

H_t is the conditional covariance matrix;

D_t is a (K×K) diagonal matrix of changing standard deviations taken from the univariate GARCH models;

R_t represents the conditional correlation matrix over time (K×K);

The matrices D_t and R_t are specified as follows:

$$D_t = diag\left(\sqrt{\sigma_{ii,t}}, \ldots\ldots, \sqrt{\sigma_{kk,t}}\right)$$

$$R_t = \left(diag(Q_t)\right)^{-\frac{1}{2}} Q_t \left(diag(Q_t)\right)^{-\frac{1}{2}}$$

Q_t=(q_(ij,t)) represents a positive symmetric (K×K) conditional covariance matrix and is written as:

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha(\mu_{t-1}\mu'_{t-1}) + \beta Q_{t-1}$$

Here, μ_{t-1} denotes the vector of standardized residuals, while $\overline{Q} = E(\mu_{t-1}\mu'_{t-1})$ represents the unconditional covariance matrix of the standardized errors μ_{it}, with dimension (K×K). The parameters α and β are unknown coefficients to be estimated within the model. To ensure that the conditional covariance matrix remains positive definite, the following parameter constraints must hold: $\alpha > 0$, $\beta \geq 0$, and $\beta + \alpha < 1$. Moreover, when $\beta + \alpha$ approaches unity, it indicates a high degree of persistence in the conditional variance dynamics.

$(Q_t)^{-\frac{1}{2}}$ denotes a diagonal matrix composed of the square roots of the inverses of the diagonal elements of $(Q_t)^{-\frac{1}{2}}$:

$$\left(diag(Q_t)\right)^{-\frac{1}{2}} = diag\left(\frac{1}{\sqrt{q_{ii,t}}} \ldots\ldots \frac{1}{\sqrt{q_{mn,t}}}\right)$$

The dynamic conditional correlation coefficient is defined as follows:

$$p_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}}, \quad i, j = 1, 2, \ldots. n, \quad / i \neq j$$

In substitution, we obtain:

$$p_{12,t} = \frac{(1-\alpha-\beta)\bar{q}_{12} + \alpha\mu_{1t-1}\mu_{2,t-1} + \beta q_{12,t-1}}{\sqrt{[(1-\alpha-\beta)\bar{q}_{12} + \alpha\mu_{1t-1}\mu_{2,t-1} + \beta q_{12,t-1}]}\sqrt{[(1-\alpha-\beta)\bar{q}_{12} + \alpha\mu_{1t-1}\mu_{2,t-1} + \beta q_{12,t-1}]}}$$

where q_{ij} represents the elements of the matrix Q_t, corresponding to row (i).

2.2. The DCC-MIDAS Model:

The Dynamic Conditional Correlation–Mixed Data Sampling (DCC-MIDAS) model, developed by Colacito et al. (2011), examines the dynamic conditional relationships between multiple variables—such as financial returns or market volatilities—while allowing for the integration of data with different temporal frequencies, both high and low. This model combines two main approaches: the DCC framework, which captures time-varying conditional correlations, and the MIDAS approach, which enables the incorporation of variables observed at mixed frequencies, such as daily (high-frequency) financial data with monthly or quarterly (low-frequency) macroeconomic data.

The DCC-MIDAS model is particularly useful for linking macroeconomic variables (e.g., economic growth rates or inflation) with financial market variables (e.g., market volatilities), providing a comprehensive framework for understanding how slow-moving macroeconomic conditions influence the high-frequency dynamics of financial assets. The DCC-MIDAS model decomposes the conditional correlations into two main components:

- **The Long-Run Component**, which captures the slowly changing correlations often associated with macroeconomic or structural factors. This component is estimated using low-frequency data (such as monthly or quarterly observations) through MIDAS weighting schemes.
- **The Short-Run Component**, which reflects daily or short-term fluctuations in correlations and is modeled using the traditional DCC dynamics.

Accordingly, the GARCH-MIDAS equation can be expressed as follows (Colacito, Engle, & Ghysels, 2011):

$$r_t = \mu_t + \sqrt{\sigma_{i,t}}.\varepsilon_t \quad \varepsilon_t \rightarrow N(0, H_t)$$

μ_t: represents the expected return of the asset;
ε_t: denotes the standardized error term;
$\sigma_{i,t}$ refers to the conditional variance of the asset, which can be expressed as follows:

$$\sigma_{i,t} = m_{it} \times g_{it}$$

m_{it}: the long-term volatility component, estimated using low-frequency data;

g_{it}: the short-term volatility component, modeled through the GARCH framework.

$$m_{it} = m + \theta \sum_{k=1}^{k} \varphi_k(\omega_1, \omega_2) R_{i,t-k}$$

m: the long-term average volatility;
$\varphi_k(\omega_1, \omega_2)$: the Beta weighting function, representing the weight assigned to each lag;
$R_{i,t-k}$: the low-frequency variable.

$$g_{it} = (1-\alpha-\beta) + \alpha \frac{(r_{i-1,t} - \mu_t)^2}{\tau_t} + \beta . g_{i-1,t}$$

$\boldsymbol{\alpha}$: the coefficient measuring the impact of past shocks;
$\boldsymbol{\beta}$: the coefficient capturing the persistence of volatility;

Accordingly, the DCC-MIDAS equation can be expressed as follows:

$$q_{xy,t} = \bar{R}(1 - \alpha - b) + a.\varepsilon_{x,t-1} \ \ \varepsilon_{y,t-1} + bq_{xy,t-1}$$

$\bar{\boldsymbol{R}}$: the unconditional correlation matrix.

$$\bar{R} = \sum_{k=1}^{k} \varphi_k(\omega_1, \omega_2)\breve{R}_{t-k}$$

$\breve{\boldsymbol{R}}_{t-k}$: the correlation matrix estimated from low-frequency data.

Results and Discussion:

This section examines the dynamic conditional relationship between S&P Green Bonds (S&PGB), Green Cryptocurrency (XRP), and the traditional financial assets — Bitcoin (BITC), Gold, Oil, S&P500, and DJI100. To achieve this, the DCC-GARCH model is employed to investigate whether shocks in traditional financial assets are dynamically transmitted to green assets, thereby assessing the potential for portfolio diversification and risk hedging. Additionally, the DCC-MIDAS model is applied to analyze the impact of Geopolitical Risk (GPR) and Climate Policy Uncertainty (CPU) on the correlations among these assets. Before conducting the econometric analysis, a descriptive statistical examination of the data is performed to provide insights into the stylized facts of the assets under study.

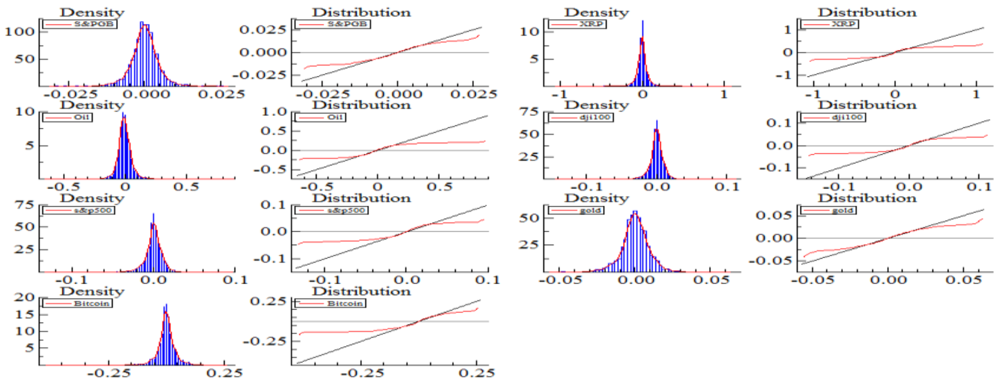
Table (1): Descriptive Statistics of the Selected Assets over the Period 2014–2025

	S&PGB	XRP	BITC	DJI100	S&P500	GOLD	OIL	GPR	CPU
Mean	2.71E-05	0.0019	0.0017	0.0004	0.0004	0.0004	-0.0002	109.02	187.49
Median	7.44E-05	0.0000	0.0014	0.0006	0.0007	0.0003	-0.0037	103.85	174.20
Maximum	0.025163	1.0279	0.2408	0.1076	0.0909	0.0577	0.8577	318.95	593.26
Minimum	-0.029623	-1.0033	-0.4972	-0.1384	-0.1276	-0.0511	-0.6222	58.420	49.125
Std. Dev.	0.004414	0.0929	0.0396	0.0111	0.0114	0.0095	0.0633	35.148	99.054
Skewness	-0.088207	1.3801	-0.9273	-0.8408	-0.6572	-0.1550	1.7563	2.2008	1.5020
Kurtosis	6.702797	31.480	17.023	24.951	18.871	6.4043	29.347	11.886	6.3486
Jarque-Bera	1499.004	89312	21828	52872	27665	1274.6	77071.3	116.365	116.36
Probability	0.000000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.00000	0.0000
ARCH Test	168.4818	638.06	76.211	569.30	673.10	33.084	64.040	-	-

The results presented in Table (1) reveal a noticeable volatility in the time series of the studied assets, indicating a relative instability during the examined period. The negative skewness values observed for the returns of S&PGB, BITC, DJI100, S&P500, and GOLD suggest a left-skewed distribution, implying a higher probability of recurring gains. In contrast, the XRP exhibits positive skewness, indicating a greater likelihood of achieving higher returns.

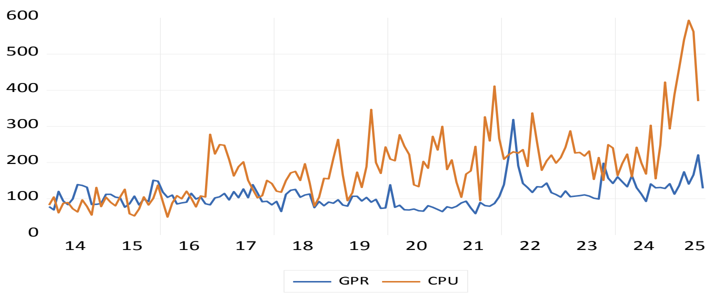
Additionally, the presence of fat tails is evident, as the kurtosis coefficients exceed the value of three, corresponding to a normal distribution. This implies that the return series deviate from normality, with a stronger concentration of values around the mean. This conclusion is further supported by the high Jarque–Bera test statistics, which confirm the non-normality of the return distributions during the study period. The following figure illustrates these findings.

Figure (1): Results of the Normality Test for the Returns of the Studied Assets



The high standard deviation observed for the GPR and CPU indices reflects elevated climate-related risks, significant volatility, and periods of political and economic tensions throughout the study period. The following figure illustrates the evolution of both indices.

Figure (2): Evolution of GPR and CPU during the Study Period



Similarly, from Table (1), it can be inferred that there exists an ARCH effect in the residual series of the studied time series. This indicates that the return variances are not constant over time, justifying the application of GARCH-type models, which are suitable for estimating conditional volatility and the dynamic conditional relationships among variables. It is also essential to verify the stationarity of the series; therefore, the ADF and PP unit root tests are employed, as presented in the following table:

Table (2): Results of the Stationarity Tests (ADF and PP) for the Return Series of the Studied Assets

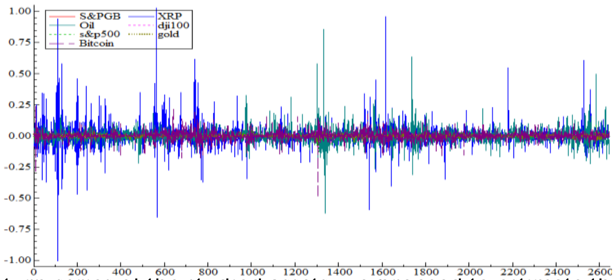
	ADF	PP
	Constant, Linear Trend	Constant, Linear Trend
S&PGB	-46.81327	-46.94556
XRP	-35.72543	-64.72765
BITC	-52.52197	-52.51008
DJI100	-16.41940	-58.35026
S&P500	-16.48140	-58.67822
GOLD	-52.62228	-52.88271
OIL	-54.07970	-55.76021

GPR	-5.6600	-5.6590
CPU	-6.1259	-6.2507

The results presented in Table (2) indicate the absence of a unit root in the data series, confirming that all return series are stationary at level.

Figure (3) provides an initial insight into the dynamic behavior and potential interconnectedness or contagion effects among the studied financial assets.

Figure (3): Daily Return Movements of the Studied Assets during the Study Period



After diagnosing the return series of the studied assets, we proceed to estimate the GARCH models, as this represents a fundamental step toward implementing the DCC-GARCH framework.
The results are summarized in the following table:

Table (3): Estimation Results of the GARCH(1,1) Model for Asset Returns

	S&PGB	XRP	BITC	S&P500	Djim100	Gold	Oil
C	7.54E-05**	-0.00114	0.001726	0.00080**	0.000693***	0.000105	-0.000272
AR(1)	0.04477	-0.10394**	0.00817	-0.05627**	-0.019034	0.00020	-0.05717***
ω	1.13E-07***	0.00029***	9.23E-05***	3.76E-06***	3.97E-06***	0.53793	0.00029***
α	0.04597***	0.15399***	0.07774***	0.179483***	0.17515***	0.02245**	0.17469***
β	0.94882***	0.83075***	0.86404***	0.79335***	0.78930***	0.97138***	0.76081***
α+β	0.9947	0.9846	0.9417	0.9727	0.9644	0.9937	0.9454

(**) and (***) indicate statistical significance at the 1% and 5% levels, respectively.

The results presented in the table above indicate that the GARCH (1,1) model is statistically valid for all return series. The α coefficient reflects the presence of a shock effect on the volatility of the studied assets. It is observed that the DJI100 index exhibits a relatively high value for this coefficient (0.1751), suggesting that its volatility is highly sensitive to market events.

In contrast, gold shows a lower α value but a higher β coefficient compared to other assets. This implies that an increase in volatility for gold tends to be followed by subsequent high volatility, indicating a strong persistence of variance over time.

The sum of the two coefficients (α + β) is close to one for all assets, with the highest value observed for green bonds (0.948). This indicates a high persistence of conditional volatility over time, meaning that volatility shocks tend to dissipate slowly.

Such behavior confirms the presence of the volatility clustering phenomenon, where periods of high variance are typically followed by subsequent periods of high variance. Consequently, the impact of shocks tends to persist indefinitely rather than vanish quickly.

- **Estimation of the DCC-GARCH Model:**

Table (4) presents the results of the Dynamic Conditional Correlation (DCC-GARCH) model estimated for the volatility of the studied asset returns. The model is statistically valid, based on Engle's (2002) methodology, and the findings reveal the presence of time-varying positive conditional correlations between the volatilities of green bond and gold returns.

This implies that events influencing fluctuations in gold returns tend to have a similar directional impact on green bond returns. This relationship implies that factors like economic uncertainty, monetary policy changes, and the growing emphasis on sustainability jointly affect both assets.

Traditionally, gold has been regarded as a safe-haven asset, attracting investors during periods of economic or financial turmoil. Similarly, green bonds, which focus on financing sustainable projects, may appeal to investors seeking relatively secure investments with environmental benefits. Consequently, during periods of heightened uncertainty such as economic crises or geopolitical tensions the demand for both assets tends to rise, leading to a positive dynamic correlation between them.

The results also reveal the presence of negative dynamic conditional correlations between the volatilities of green bond returns and oil returns. This finding implies that green bonds serve as a hedging instrument against oil market risks during the study period. In other words, investors appear to have utilized green bonds within their portfolios to offset potential losses arising from fluctuations in oil prices.

We observe a similar result for the green cryptocurrency, showing a negative correlation with Bitcoin. This suggests that the green cryptocurrency functioned as an effective hedge against Bitcoin throughout the study period, providing diversification benefits and reducing portfolio risk exposure.

The results further indicate an absence of sensitivity between green bonds, green cryptocurrency, and stock market indices, as evidenced by the statistical insignificance of the estimated parameters. This suggests that no contagion effects exist among these assets that is, shocks affecting one asset do not influence the conditional variance of green asset returns.

This finding highlights an important investment opportunity for investors, as green assets can be used to enhance portfolio returns, minimize overall risk, and protect capital, particularly when investing in the green bond market. The lack of linkage between green assets and traditional financial assets may be attributed to the fact that they do not share common price determinants, such as typical financial and macroeconomic variables. Consequently, green assets act as effective hedging instruments against traditional market exposures during the study period.

Furthermore, as shown in Table (4), the sum of the α and β coefficients equals 0.9632, indicating a high degree of persistence in the dynamic correlations over the long term.

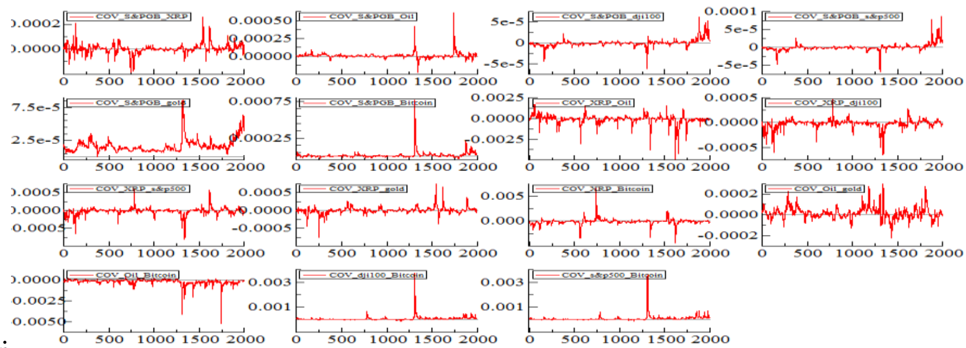
Table (4): Estimation Results of the DCC(E)-GARCH(1,1) Model for Asset Returns

	rho	α	β
S&PGB – BITC	0.0659	0.0261***	0.9371***
S&PGB - S&P500	-0.0367		
S&PGB – Gold	0.4722***		
S&PGB – Oil	-0.0259***		
S&PGB - Djim100	-0.0447		

XRP- BITC	-0.0366**		
XRP- Oil	-0.0172		
XRP- Gold	0.0001		
XRP - S&P500	-0.0210		
XRP - Djim100	-0.0227		

The following figure illustrates the dynamic conditional correlations among the studied assets:

Figure (4): Dynamic Conditional Correlations (E) among Asset Returns



- **Estimation of the GARCH-MIDAS Model**

The GARCH-MIDAS model was estimated to assess the impact of geopolitical risk (GPR) and climate policy uncertainty (CPU) on the long-term variance component of asset returns.

The results presented in the table show that the GARCH-MIDAS-GPR model is statistically significant at the 5% level. The coefficient α_1 exhibits a relatively high value, indicating a rapid short-term response of the variables to shocks and external influences. Similarly, the β_1 coefficient is also high, suggesting a strong persistence of volatility shocks over time.

The θ parameters capture the responsiveness of long-term volatility to shocks in the GPR index. The results reveal that θ is negative and statistically significant for all indices except XRP, implying that the GPR index negatively affects the long-term volatility of the studied assets. This suggests that an increase in geopolitical risk tends to reduce the long-term volatility component, potentially reflecting a shift toward more stable investment behavior in green and sustainable assets during periods of heightened uncertainty.

The results of the GARCH-MIDAS-CPU model indicate that the CPU index exerts a negative long-term effect on the return variances of S&P500, DJI100, and Gold, as reflected by the negative values of the θ parameter. This suggests that heightened climate policy uncertainty tends to dampen long-term volatility for these traditional financial assets, possibly due to a flight-to-quality behavior or a reallocation toward safer investments.

Conversely, the θ parameter is positive and statistically significant for S&PGB, XRP, BITC, and Oil, implying that climate policy uncertainty amplifies long-term volatility in these markets. This outcome highlights the sensitivity of green and energy-related assets to changes in climate policy expectations and regulatory uncertainty during the study period.

Table (5): Estimation Results of the CPU–GARCH-MIDAS Model for GPR

	GARCH-MIDAS - GPR						
	S&PGB	**XRP**	**BITC**	**S&P500**	**Djim100**	**Gold**	**Oil**
C	0.00033**	-0.00024	0.000213	0.00005**	0.000323 ***	0.000001	-0.000262
AR(1)	0.06850	-0.35215**	0.00601	-0.00365**	-0.014211	0.00045	-0.00325***
α	0.06214***	0.07019***	0.07341***	0.069964***	0.15222***	0.02456**	0.09949***

β	0.92121***	0.91255***	0.91421***	0.85365***	0.78111***	0.94253***	0.84210***
ω	2.13E-05***	0.00014***	8.13E-05***	2.16E-06***	2.96E-06***	0.53693	0.00009***
m	0.2242	0.8563	0.3021	0.5423	0.3254	0.9223	0.2465
Ø	-1.312***	0.411***	-0.312***	-0.421**	-0.907	-0.521***	-0.732***
	GARCH-MIDAS - CPU						
C	0.00001**	-0.00014	0.000215	0.00017**	0.000403 ***	0.000015	-0.000342
AR(1)	0.05670	-0.21214**	0.00751	-0.02710**	-0.028123	0.00151	-0.04123***
α	0.05124***	0.06089***	0.06547***	0.075864***	0.18122***	0.02456**	0.09949***
β	0.93431***	0.92155***	0.91104***	0.85234***	0.77512***	0.95158***	0.80101***
ω	1.03E-05***	0.00024***	2.52E-03***	3.10E-02***	2.01E-03***	0.23213	0.00001***
m	0.3122	0.7662	0.4223	0.6121	0.3254	0.9255	0.2326
Ø	1.357***	0.701***	0.283***	-1.001**	-0.102	-0.201***	1.133***

Estimation of the DCC-MIDAS Model:

The DCC-MIDAS-GPR model was estimated to capture the effect of geopolitical risk (GPR) on the long-term correlations between the study variables through the θ coefficients. The results reveal that most θ parameters are negative, indicating that increases in GPR lead to a decline in the long-term correlations among these markets. This suggests that both green bonds and the green cryptocurrency can serve as strong safe-haven assets against the S&P 500, DJIM 100, gold, and energy markets during periods of elevated GPR levels. In other words, green bonds become more attractive in times of heightened uncertainty. Geopolitical risks generate uncertainty that influences investor behavior, leading them to rebalance their portfolios toward assets perceived as safe havens namely, green bonds, which are linked to environmentally sustainable projects with long-term stability. Therefore, green bonds can be considered effective hedging instruments against geopolitical risks.

Table (6): Estimation Results of the DCC-MIDAS-GPR Model

	α	**β**	**ω**	**m**	**Ø**
S&PGB – BITC	0.025*** (0.000)	0.944*** (0.000)	2.159*** (0.455)	0.388*** (0.045)	-1.245 (0.245)
S&PGB - S&P500	0.023*** (0.000)	0.910*** (0.000)	1.165 (1.412)	0.245 (0.065)	-0.745*** (0.482)
S&PGB – Gold	0.056*** (0.000)	0.930*** (0.000)	2.143*** (1.254)	0.996*** (0.041)	-0.521*** (0.283)
S&PGB – Oil	0.032*** (0.000)	0.967*** (0.000)	1.050 (0.621)	0.133*** (0.025)	-0.741*** (0.582)
S&PGB - Djim100	0.050*** (0.000)	0.930*** (0.002)	4.461*** (0.231)	0.346 (0.037)	-1.917*** (0.645)
XRP- BITC	0.038*** (0.000)	0.938*** (0.012)	3.342*** (1.856)	0.086*** (0.053)	-0.734*** (0.475)
XRP- Oil	0.025*** (0.000)	0.912*** (0.000)	1.642 (1.242)	0.012 (0.029)	1.354*** (0.245)
XRP- Gold	0.041*** (0.000)	0.946*** (0.000)	1.350*** (0.310)	0.045*** (0.041)	0.750 (0.489)
XRP - S&P500	0.036*** (0.000)	0.932*** (0.000)	3.134** (1.706)	0.145 (0.013)	-1.945*** (0.589)
XRP - Djim100	0.029*** (0.000)	0.921*** (0.000)	1.165** (1.186)	0.075 (0.003)	-1.840*** (0.156)

The DCC-MIDAS-CPU model was also estimated, where the coefficient θ captures the impact of climate policy uncertainty (CPU) on the long-term correlations among assets.

Table (7) shows that the θ coefficients are significantly negative in the correlations between S&PGB and S&P500, Djim100, and Oil, indicating that an increase (decrease) in climate policy uncertainty leads to a decrease (increase) in the long-term correlations among these assets.

However, the magnitude of these effects varies across low-carbon assets, depending on their specific asset class characteristics. In contrast, the θ coefficients are positive in the correlations involving BITC and Gold, suggesting that higher climate policy uncertainty strengthens their long-term linkages.

Furthermore, the table reveals that θ is negative for the correlations of XRP with S&P500 and DJIM 100, as well as for the correlations between the cryptocurrency index and other studied variables.

Table (7): Estimation Results of the DCC-MIDAS-CPU Model

	α	β	ω	m	Ø
S&PGB – BITC	0.029*** (0.000)	0.932*** (0.000)	1.241*** (0.326)	0.128*** (0.022)	0.462*** (0.194)
S&PGB - S&P500	0.024*** (0.000)	0.921*** (0.000)	1.101 (1.261)	0.176 (0.005)	-0.810*** (0.310)
S&PGB – Gold	0.043*** (0.000)	0.933*** (0.000)	2.341*** (1.321)	0.840*** (0.052)	0.742*** (0.348)
S&PGB – Oil	0.033*** (0.000)	0.961*** (0.000)	4.221 (0.301)	0.261*** (0.031)	-0.470*** (0.810)
S&PGB - Djim100	0.048*** (0.000)	0.939*** (0.002)	1.263*** (0.432)	0.346 (0.037)	-0.823 (0.645)
XRP- BITC	0.031*** (0.000)	0.930*** (0.012)	3.191*** (1.723)	0.041*** (0.041)	0.616*** (0.341)
XRP- Oil	0.027*** (0.000)	0.922*** (0.000)	1.401 (1.153)	0.022 (0.055)	0.761*** (0.361)
XRP- Gold	0.035*** (0.000)	0.949*** (0.000)	2.463*** (0.471)	0.051*** (0.062)	0.612 (0.841)
XRP - S&P500	0.031*** (0.000)	0.940*** (0.000)	2.821** (1.135)	0.211 (0.021)	0.750 (0.410)
XRP - Djim100	0.032*** (0.000)	0.901*** (0.002)	1.532** (0.240)	0.021 (0.014)	-1.621*** (0.271)

The results of the study indicate that the distribution of returns for the examined assets exhibits a leptokurtic pattern, reflecting the presence of fat-tail behavior and the deviation of the time series from normality during the study period. This finding suggests a heightened level of risk and instability in the behavior of green financial markets. These results are consistent with the findings of (Kuang, 2025) and (Kılıç & Altan, 2023), both of which confirmed that certain green assets—particularly green cryptocurrencies—can help mitigate tail risks and enhance portfolio resilience during periods of market stress and uncertainty. Hence, the present study complements the existing literature by highlighting the nonlinear nature of return distributions amid evolving environmental and financial market dynamics.

The results also reveal a persistence of conditional volatility among the examined assets, indicating that the effects of market shocks extend into future periods before gradually dissipating. This finding is partially consistent with the results of (Kocaarslan, 2021), who noted that the behavior of green asset returns is characterized by sustained volatility and a slow reversion to stability. Such dynamics reflect a high degree of sensitivity to global economic and financial developments, underscoring the enduring impact of external shocks on green financial markets.

Regarding the interrelationships among assets, the results reveal positive dynamic conditional correlations over time between the volatilities of green bond returns and gold, indicating that changes in one asset tend to move in the same direction as the other. This co-movement suggests that both assets are jointly influenced by macroeconomic factors such as economic uncertainty, monetary policy shifts, and the growing global emphasis on sustainability. This finding is consistent with (Naeem, Adekoya, & Oliyide, 2021), who documented long-term linkages between green bonds and gold, emphasizing their interconnected behavior under conditions of financial and environmental uncertainty.

Conversely, the results reveal negative dynamic conditional correlations between the volatilities of green bond returns and oil prices, indicating that green bonds serve a hedging role against oil market risks during periods of instability. This finding aligns with (Zhang, Hong, & Ding, 2023), who demonstrated that the volatility of green assets tends to move inversely with that of high-emission traditional assets, thereby reinforcing the dual function of green bonds as both environmental and financial hedging instruments in times of heightened uncertainty.

The study also found that green cryptocurrencies exhibited a negative correlation with Bitcoin, suggesting that they functioned as hedging instruments against Bitcoin's volatility during the study period. This result is consistent with the findings of (Hung, 2021), who supported the existence of an inverse relationship between green and conventional cryptocurrencies. However, it contrasts with the conclusions of (Haq, Chupradit, & Huo, 2021), who observed a positive short-term relationship between the two asset classes.

In another context, the findings revealed that green bonds and green cryptocurrencies were primarily utilized by investors as key instruments for hedging against stock market index risks. The absence of statistically significant relationships among these variables indicates a promising investment opportunity for enhancing portfolio returns and reducing overall risk exposure. This result partially aligns with the findings of (Imran & Ahad, 2023), (Yadav, Mishra, & Ashok, 2023), and (Haq, Maneengam, & et al, 2023), who demonstrated that green assets—particularly green bonds—serve as effective short-term tools for diversification and hedging, despite their diminishing effectiveness over the long term. Furthermore, (Haq, Maneengam, & et al, 2023) showed that digital green bonds exhibit wave-based interconnections with non-green cryptocurrencies, reflecting a new dynamic structure in the relationships between green and traditional assets. Accordingly, the present study extends the existing body of knowledge by highlighting the time-varying hedging role of green assets and emphasizing their potential in enhancing portfolio management efficiency through temporal diversification effects.

Finally, the study found that both Geopolitical Risk (GPR) and Climate Policy Uncertainty (CPU) exert a negative impact on the correlations among the examined assets, indicating that green bonds and green cryptocurrencies acquire safe-haven characteristics during periods of elevated risk. This finding is consistent with the results of (Dong, Xiong, & et al, 2023), who demonstrated that rising levels of Geopolitical Risk (GPR) and Climate Policy Uncertainty (CPU) reduce inter-asset correlations, thereby enhancing the capacity of green assets to absorb shocks and safeguard investment portfolios amid periods of geopolitical and environmental instability.

Conclusion:

The Paris Climate Agreement of 2015 and the United Nations Sustainable Development Goals (SDGs) have significantly enhanced global awareness of the importance of environmental protection and sustainability, encouraging investors to turn toward green assets in financial markets as investment instruments that integrate environmental and social considerations. With the expansion of the green finance market, academic interest has increasingly focused on the potential role of these assets in risk management and portfolio diversification, as several researchers argue that they may serve as safe-haven instruments during periods of financial market volatility and global uncertainty.

This study aims to explore the distinctive investment role of green assets over the period 2014–2025, by examining their hedging capabilities and safe-haven properties amid financial, economic, and geopolitical crises. The findings have important implications for investors and policymakers. Regardless of geopolitical, economic, or climate policy risks, investors tend to favor green bonds due to their inherent environmental stability, enabling them to hedge against tail risks and preserve returns during turbulent periods.

Moreover, the results indicate that investor preferences toward assets are shaped by the nature and predictability of risks, while media reports and policy announcements play a crucial role in influencing investor sentiment and investment behavior. Accordingly, investors may design trading strategies based on sentiment indices and market preference signals, which could potentially outperform traditional investment strategies in the short term, particularly in environments characterized by heightened geopolitical and climate-related uncertainty.

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