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Decoding the Sustainability-Finance Nexus: Green Bonds and Their Interactions with Global Financial Indicators

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Abstract
This study explores the dynamic interactions between green bonds and major global financial indicators, green bonds, global commodity and equity indices, Bitcoin, crude oil, and US dollar index, employing Granger causality tests and a Vector Autoregression (VAR) framework. The empirical results underscore the responsiveness of green bonds, represented by the S&P Green Bond Index (SPGB), to global equity market movements, particularly the MSCI Global Equity Index (MSCIE). A strong unidirectional causality from MSCIE to SPGB suggests that green bond performance is shaped significantly by trends in global equity markets, reflecting broader macroeconomic sentiment and capital availability for sustainable investments. Additionally, the bidirectional causality between MSCIE and the US Dollar Index (USDX) illustrates the tight interlinkage between currency dynamics and global equity flows. In contrast, the analysis finds no significant causal relationship between green bonds and more speculative or volatile assets such as crude oil and Bitcoin, likely due to differences in investor profiles, investment horizons, and market structures. The VAR results further validate that green bonds are primarily influenced by their own lags and by equity and currency markets, with limited influence on other assets. These findings suggest that green bonds currently play a reactive rather than leading role in the global financial ecosystem, shaped by their emerging status, relatively lower liquidity, and alignment with ESG-focused investment mandates.
Keywords - *Green Bonds, Global Equity Index, US Dollar Index, Crude Oil, Bitcoin, Sustainable Finance, Financial Market Integration*

1. INTRODUCTION

The intersection of sustainability and finance has garnered significant academic and policy interest in recent years, particularly with the emergence of green bonds as a pivotal instrument in mobilizing capital for climate-resilient infrastructure and environmentally sustainable development. Green bonds—debt securities issued to finance projects with positive environmental outcomes—have evolved from niche financial products into globally recognized vehicles supporting the transition to a low-carbon economy. As climate change, environmental degradation, and energy transition dominate global economic discourse, understanding the dynamic interactions of green bonds with traditional and emerging financial indicators has become crucial.

The literature increasingly emphasizes the complex linkages between green bonds and key financial variables, including oil prices, cryptocurrencies, renewable energy indices, and environmental risk factors. For instance, Yadav et al. (2025) demonstrated that green bonds, while receiving volatility spillovers from renewable energy and crypto markets, provide limited short-term diversification but exhibit stronger interdependence over longer horizons. Similarly, Zeng et al. (2025) reported intensified return connectedness between green bonds and both green energy-related metals and cryptocurrencies, particularly in the post-COVID-19 period. This interconnectedness suggests that green bonds are not insulated from broader financial market dynamics and may serve both as recipients and transmitters of risk.

Moreover, oil and energy markets significantly influence green bond performance. Empirical evidence points to negative volatility spillovers from crude oil to green bonds (Yousaf et al., 2024), while certain studies find green bonds acting as effective hedging instruments against oil price shocks (Huang et al., 2022). Wang et al. (2023) uncovered asymmetric and quantile-dependent relationships between oil prices and green bond indices, further highlighting the contextual sensitivity of this nexus. Additionally, the role of cryptocurrencies—especially Bitcoin—has gained traction. Wang et al. (2024) noted long-term significant effects of Bitcoin prices on the Chinese green bond market, underscoring the need for regulatory oversight to safeguard green finance from crypto-induced volatility.

Environmental and geopolitical risks also shape green bond dynamics. Mejri et al. (2025) established that green bonds offer long-term stability under geopolitical stress, functioning as defensive assets in diversified portfolios. Meanwhile, Kartal et al. (2024) and Marín-Rodríguez et al. (2022) emphasized the feedback mechanisms between green bonds, CO_2 emissions, and environmental degradation, revealing the role of green bonds not just as financial tools but as environmental signals.

Against this backdrop, decoding the sustainability-finance nexus requires a granular understanding of how green bonds interact with global financial indicators across time and frequency domains. This investigation is essential for investors, policymakers, and regulators aiming to leverage green bonds as tools for financial resilience and environmental sustainability. The present study seeks to contribute to this emerging discourse by mapping these multifaceted relationships, thereby illuminating the positioning of green bonds in the global financial ecosystem.

2. LITERATURE REVIEW

The growing prominence of green bonds as a tool for sustainable finance has attracted extensive empirical investigation into their interrelationship with various financial and commodity markets. A substantial body of literature has examined these dynamics across different frequencies, market conditions, and asset classes (Fernandes et al., 2023; Hasan et al., 2024; Cagli et al., 2023; Nguyen et al., 2021; Ahmed and Kaur, 2025; Tsagkanos et al., 2022; Mezghani et al., 2025; Kocaarslan, 2021; Ghanbari, 2024; Mensi et al., 2023; Kaur and Ahmed, 2025).

Yadav et al. (2025) explored the time- and frequency-domain interlinkages between green bonds, renewable energy indices, and cryptocurrencies using dynamic conditional correlation (DCC), Diebold and Yilmaz (2012) spillover index, and the Baruník and Křehlík (2018) frequency spillover model. Their findings suggest that green bonds act as net receivers of volatility spillovers, especially in longer horizons, indicating reduced diversification potential in the long term. Similarly, Zeng et al. (2025) applied advanced methodologies including TVP-VAR, wavelet coherence, and quantile-based connectedness models to assess co-movements among green bonds, cryptocurrencies, and green-energy-related metals. They found stronger connectedness post-COVID-19, with green bonds being net recipients of return spillovers.

Focusing on the impact of Bitcoin, Wang et al. (2024) employed the quantile autoregressive distributed lag (QARDL) model to assess the asymmetric impact of Bitcoin prices on Chinese green bonds. Their results confirmed significant long-term effects, highlighting the necessity of policy interventions to buffer market shocks from volatile crypto assets. Hassan et al. (2022) also investigated the spillover effects of cryptocurrency environmental attention on green bonds and ESG-related stocks using wavelet and quantile regression techniques, identifying negative impacts on green bonds during periods of heightened attention.

In a geopolitical context, Mejri et al. (2025) used wavelet-based quantile analyses and portfolio optimization to examine the responses of green bonds, gold, and Bitcoin to geopolitical risk shocks. Their study revealed green bonds as stable long-term assets, with greater defensive capacity during uncertainty, particularly in variance-minimizing portfolios.

Oil market dynamics also play a significant role in the behaviour of green bonds. Yousaf et al. (2024) found short-term spillovers from oil to green bonds using the BK-18 framework, DCC-GARCH, and wavelet coherence. The negative volatility spillovers further supported green bonds as a hedge against oil shocks. Wang et al. (2023) confirmed this asymmetric relationship through rolling-window and quantile-based Granger causality tests, indicating that high oil prices affect green bond indices more severely. In a similar line, Azhgaliyeva et al. (2022) analyzed the effects of various oil shocks—supply, demand, and speculative—on corporate green bond issuance using multilevel models, concluding that such shocks significantly influence issuance probabilities but not issuance shares.

Exploring the safe-haven role of green bonds, Huang et al. (2022) compared their performance with precious metals under extreme conditions using the Baur and McDermott (2010) framework. They concluded that green bonds serve as strong hedges and safe havens, especially during crises like COVID-19 and geopolitical conflict, outperforming traditional safe assets like gold and silver. Abakah et al. (2023), using GARCH-family models and frequency-domain causality tests, found green bonds to be effective hedges against gas price volatility, especially shale gas, and highlighted their potential to support low-carbon transitions.

Environmental variables such as CO_2 emissions have also been analysed in relation to green bonds. Marín-Rodríguez et al. (2022) used DCC-GARCH and Granger causality approaches to identify unidirectional causality from green bonds to oil and CO_2 futures, reinforcing the role of green bonds as market influencers during crises. Kartal et al. (2024) employed the WLMC method in a sectoral context and confirmed that green bonds significantly affect environmental degradation metrics, particularly CO_2 emissions, albeit with variations across time and frequency domains.

3. RESEARCH METHODOLOGY

3.1 Johansen Cointegration

The Johansen co-integration test, introduced by Johansen in 1988 and 1991, is a multivariate method designed to assess the presence of long-term equilibrium relationships among non-stationary time series variables that are integrated to the same degree, typically I *(1).* In contrast to the Engle-Granger two-step approach, which is limited to two variables, the Johansen test is capable of handling multiple time series, making it more robust in multivariate contexts.

The methodology is based on the VAR model of order p.

$$X_t = A_1 X_{t-1} + A_2 X_{t-2} + \cdots + A_p X_{t-p} + \varepsilon_t$$

(1)

where X_t is an *n×1* vector of non-stationary I (1) variables, Ai are coefficient matrices, and ε is a vector of white noise processes. The Johansen method reformulates this VAR model into a VECM:

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \varepsilon_t$$

(2)

In the Johansen co-integration framework, the VAR model is transformed into a VECM to capture both the short-run and long-run dynamics of the system. In this representation, ΔX_t denotes the differenced series of the original non-stationary variables, capturing short-term changes. The matrix $\Pi = \sum_{i=1}^{p} A_i - I$ is referred to as the long-run impact matrix, and it contains crucial information about the existence and number of co-integrating relationships among the variables. The matrices $\Gamma_i = -\sum_{j=i+1}^{p} A_j$ represent the short-run adjustment dynamics.

The central component of the Johansen test is the rank of the matrix Π. If rank $(\Pi) = 0$, there is no co-integration among the variables, implying that they do not share a long-run equilibrium relationship. When $0 < rank(\Pi) = r < n$, it suggests the presence of r co-integrating vectors, meaning that r linear combinations of the variables are stationary despite the individual series being non-stationary. If rank $(\Pi) = n$, it indicates that all variables in the system are stationary in levels. To determine the number of co-integrating relationships, the Johansen procedure employs two likelihood ratio test statistics: the trace statistic and the maximum eigenvalue statistic. The trace statistic is defined as:

$$\text{Trace statistic}(r) = -T \sum_{i=r+1}^{n} \ln\left(1 - \hat{\lambda}_i\right) \quad (3)$$

where T is the sample size, and $\hat{\lambda}_i$ are the estimated eigenvalues derived from the Π matrix. This statistic tests the null hypothesis that the number of co-integrating vectors is less than or equal to r, against a general alternative.

4. RESULTS AND ANALYSIS

The descriptive statistics, in table 1 reveal distinct characteristics across the selected financial variables. Green bonds (RSPGB) exhibit a near-zero mean return (-0.0018) with moderate volatility, indicating stability but a slight left skew and high kurtosis, suggesting occasional extreme losses. The Global Commodity Index (RSPGCI) shows a negative average return with high variability and extremely high kurtosis (16.12), implying frequent large price swings. The US Dollar Index (RUSDX) is relatively stable with a modest positive mean and low volatility, showing minimal skewness and moderate tail risk. In contrast, the Global Equity Index (RMSCIE) displays a positive average return but is highly volatile, left-skewed, and leptokurtic, pointing to the possibility of large downside movements. Bitcoin (RBTC) stands out with extreme volatility and the highest kurtosis (17.83), driven by large outliers and a positive skew. Crude oil (ROIL) is also volatile, with a slight negative mean and heavy tails. Overall, the data reflect significant non-normality and high-risk characteristics, especially in RBTC and RSPGCI. Further, all the series were found to be non-stationary at the level, pre-requisite for the

Table 1 - Descriptive Statistics

Statistic	RSPGB (Green Bonds)	RSPGCI (Global Commodity Index)	RUSDX (US Dollar Index)	RMSCIE (Global Equity Index)	RBTC (Bitcoin)	ROIL (Crude Oil)
Mean	-0.001805	-0.020016	0.006571	0.152714	26.86373	-0.010274
Median	0.010000	0.360000	0.000000	0.300000	1.100000	0.050000
Maximum	2.730000	134.6500	2.280000	32.23000	12146.80	8.890000
Minimum	-3.410000	-107.8900	-2.370000	-45.05000	-7955.300	-16.60000
Std. Dev.	0.484632	14.28747	0.417709	4.744757	1124.397	1.570452
Skewness	-0.255962	-0.169250	-0.129282	-0.863528	0.312550	-0.773404
Kurtosis	7.175942	16.11910	5.534274	11.95440	17.83531	12.12225

Source – Author's Work

4.1 Johansen Cointegration Test

The Johansen cointegration test was conducted to examine the presence of any long-run equilibrium relationship among six variables: Green Bonds RSPGB, RSPGCI, RUSDX, RMSCIE, RBTC, and ROIL. The results indicate that the trace statistic for the null hypothesis of no cointegrating equation is 93.47, which is slightly below the 5% critical value of 95.75, with a p-value of 0.0711. Since this p-value is greater than the 0.05 threshold, we fail to reject the null hypothesis. Similarly, for all subsequent hypotheses (from "at most 1" to "at most 5" cointegrating equations), the trace statistics are significantly lower than their respective critical values, and the associated p-values remain high, further supporting the absence of cointegration. Therefore, the analysis concludes that there is no statistically significant long-run equilibrium relationship among the selected variables, although short-run interdependencies may still exist.

Table 2 - Johansen Cointegration Test
Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.014233	93.46898	95.75366	0.0711
At most 1	0.007325	49.93355	69.81889	0.6407
At most 2	0.004651	27.60524	47.85613	0.8304
At most 3	0.003201	13.44826	29.79707	0.8701
At most 4	0.001220	3.711082	15.49471	0.9254
At most 5	8.74E-07	0.002653	3.841466	0.9564

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

The Johansen cointegration test using the Max-Eigenvalue statistic provides further insights into potential long-run relationships among the six variables: Green Bonds, Global Commodity Index, US Dollar Index, Global Equity Index, Bitcoin, and Crude Oil. The test reveals that the Max-Eigenvalue statistic for the null hypothesis of no cointegrating equation is 43.54, which exceeds the 5% critical value of 40.08, with a p-value of 0.0196. This indicates a statistically significant result at the 5% level, suggesting the presence of at least one cointegrating relationship. However, for all subsequent hypotheses (from "at most 1" to "at most 5"), the Max-Eigen statistics fall well below their respective critical values, and the associated p-values are considerably higher than 0.05, implying no additional cointegrating vectors. In summary, the Max-Eigenvalue test suggests the existence of a single long-run equilibrium relationship among the variables.

Table 3 - Table Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None*	0.014233	43.53543	40.07757	0.0196
At most 1	0.007325	22.32831	33.87687	0.5822
At most 2	0.004651	14.15697	27.58434	0.8116
At most 3	0.003201	9.737181	21.13162	0.7689
At most 4	0.001220	3.708429	14.26460	0.8888
At most 5	8.74E-07	0.002653	3.841466	0.9564

Max-eigenvalue test indicates 1 cointegrating equation(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

4.2 VAR Results

The Vector Autoregression (VAR) results provide insights into the dynamic interrelationships among the six studied variables. The coefficients, standard errors, and t-statistics (in brackets) suggest both significant and insignificant influences across lagged variables.

Focusing on the equation for RSPGB, its own first lag has a significantly negative impact (coefficient = -0.1227, t = -4.76), indicating a strong mean-reverting behaviour. RSPGB also responds negatively to its second lag and the first lag of RUSDX (t = -3.27), suggesting that a stronger dollar index reduces green bond returns. RMSCIE(-2) has a positive and significant effect, highlighting some delayed influence from global equities. In the RSPGCI equation, its own lags are highly significant (t = 6.70 and 4.18), implying strong autoregressive behavior. Other variables, however, exert limited influence. The US Dollar Index is significantly affected by its own lags and by RMSCIE(-1), which has a strong negative impact (t = -5.08), indicating that rising equity markets may dampen the dollar.

RMSCIE shows strong self-dependence (t > 3.8) and is also positively influenced by RSPGB(-2) and RUSDX(-1), suggesting feedback from green bonds and the dollar. Bitcoin (RBTC) displays minimal significant influence across the system except for its own lag (RBTC(-1), t = -2.75), reflecting volatility with limited spillover effects. Crude oil (ROIL) reacts significantly to its own second lag (t = -2.22) and RSPGB(-1), implying some backward-looking response and weak connections with green bonds. Overall, the system is marked by significant own-lag effects, weak cross-variable spillovers, and meaningful interdependence particularly between green bonds, dollar index, and global equities.

Table 4 - VAR Results

Variable	RSPGB	RSPGCI	RUSDX	RMSCIE	RBTC	ROIL
RSPGB(-1)	-0.122660 (0.02575) [-4.76271]	0.165310 (0.77754) [0.21261]	-0.074678 (0.02287) [-3.26602]	-0.476827 (0.25986) [-1.83495]	-17.47612 (61.4932) [-0.28420]	0.092238 (0.08640) [1.06760]
RSPGB(-2)	-0.015495 (0.02465) [-0.62868]	1.277313 (0.74410) [1.71659]	-0.010109 (0.02188) [-0.46199]	0.499491 (0.24868) [2.00855]	86.80599 (58.8483) [1.47508]	-0.079571 (0.08268) [-0.96238]
RSPGCI(-1)	0.000818 (0.00060) [1.36276]	0.121317 (0.01812) [6.69513]	-0.000515 (0.00053) [-0.96617]	0.001170 (0.00606) [0.19319]	0.829881 (1.43306) [0.57910]	0.001652 (0.00201) [0.82051]
RSPGCI(-2)	-0.000937 (0.00060) [-1.56362]	0.075554 (0.01810) [4.17534]	0.000968 (0.00053) [1.81868]	0.003105 (0.00605) [0.51345]	0.968475 (1.43109) [0.67674]	0.002577 (0.00201) [1.28143]
RUSDX(-1)	-0.292816 (0.02881) [-10.1643]	0.143369 (0.86975) [0.16484]	-0.075008 (0.02558) [-2.93269]	-0.768339 (0.29067) [-2.64331]	16.24605 (68.7851) [0.23619]	0.193086 (0.09664) [1.99796]

RUSDX(-2)	-0.059770 (0.02921) [-2.04606]	0.906678 (0.88194) [1.02805]	-0.029605 (0.02594) [-1.14149]	0.056728 (0.29475) [0.19246]	57.73459 (69.7492) [0.82775]	0.078638 (0.09800) [0.80246]
RMSCIE(-1)	0.016523 (0.00197) [8.37335]	-0.081539 (0.05958) [-1.36865]	-0.008898 (0.00175) [-5.07894]	0.075743 (0.01991) [3.80416]	2.447166 (4.71166) [0.51939]	0.016218 (0.00662) [2.44988]
RMSCIE(-2)	0.004418 (0.00200) [2.20686]	-0.016959 (0.06044) [-0.28061]	0.002905 (0.00178) [1.63459]	0.041172 (0.02020) [2.03840]	2.161160 (4.77966) [0.45216]	0.015757 (0.00672) [2.34647]
RBTC(-1)	1.90E-07 (7.9E-06) [0.02417]	0.000411 (0.00024) [1.72668]	4.72E-06 (7.0E-06) [0.67504]	0.000127 (7.9E-05) [1.59272]	-0.051786 (0.01881) [-2.75309]	2.49E-05 (2.6E-05) [0.94295]
RBTC(-2)	-1.55E-05 (7.9E-06) [-1.96438]	-0.000130 (0.00024) [-0.54395]	1.24E-05 (7.0E-06) [1.77213]	-3.88E-05 (8.0E-05) [-0.48675]	0.019337 (0.01885) [1.02563]	-1.06E-05 (2.6E-05) [-0.40205]
ROIL(-1)	-0.014161 (0.00557) [-2.54148]	0.010685 (0.16822) [0.06352]	-0.003979 (0.00495) [-0.80444]	-0.050045 (0.05622) [-0.89017]	9.309275 (13.3039) [0.69974]	0.008946 (0.01869) [0.47860]
ROIL(-2)	-0.002545 (0.00558) [-0.45590]	-0.021508 (0.16857) [-0.12759]	-0.004210 (0.00496) [-0.84927]	0.080817 (0.05634) [1.43457]	3.590330 (13.3313) [0.26932]	-0.041624 (0.01873) [-2.22231]
C	-0.002405 (0.00849) [-0.28318]	-0.019904 (0.25638) [-0.07763]	0.007863 (0.00754) [1.04298]	0.139253 (0.08568) [1.62522]	27.30044 (20.2760) [1.34644]	-0.017795 (0.02849) [-0.62465]

4.3 Granger Causality Results

The Granger causality test examines whether past values of one variable help predict another. The results indicate that most relationships among the variables are statistically insignificant at the 5% level. Specifically, there is no evidence of bidirectional Granger causality between Green Bonds and Global Commodity Index, Crude Oil, or Bitcoin, as all p-values exceed 0.05. However, Global Equity Index significantly Granger-causes Green Bonds ($F = 18.11$, $p < 0.01$), suggesting that movements in global equities help predict green bond returns, but the reverse is not true. There is also no significant causality between USD Index and SPGCI, nor between USDX and Oil, or Bitcoin. Interestingly, MSCIE Granger-causes USDX ($F = 8.31$, $p < 0.01$), and USDX Granger-causes MSCIE ($F = 3.19$, $p = 0.0071$), indicating a bidirectional relationship between equity markets and the dollar index. Similarly, SPGCI Granger-causes BTC ($p = 0.0492$), suggesting that commodity prices may influence Bitcoin in the short run. Lastly, MSCIE Granger-causes Oil ($p = 0.0214$), but not the other way around.

Overall, the results highlight the predictive power of global equity markets across multiple variables, including green bonds, oil, and the dollar index. However, green bonds themselves appear to have limited predictive influence, emphasizing their role more as a dependent variable within the system.

Table 5 Granger Causality

Null Hypothesis	F-Statistic	Prob.
SPGCI does not Granger Cause SPGB	1.08740	0.3651
SPGB does not Granger Cause SPGCI	1.07558	0.3718
OIL does not Granger Cause SPGB	1.85845	0.0983
SPGB does not Granger Cause OIL	1.48262	0.1920

MSCIE does not Granger Cause SPGB	18.1131	9.E-18
SPGB does not Granger Cause MSCIE	1.75059	0.1197
BTC does not Granger Cause SPGB	2.19444	0.0522
SPGB does not Granger Cause BTC	0.85212	0.5127
USDX does not Granger Cause SPGCI	0.93430	0.4574
SPGCI does not Granger Cause USDX	0.90814	0.4746
OIL does not Granger Cause SPGCI	0.07574	0.9959
SPGCI does not Granger Cause OIL	0.88165	0.4924
MSCIE does not Granger Cause SPGCI	1.23151	0.2915
SPGCI does not Granger Cause MSCIE	1.13572	0.3390
BTC does not Granger Cause SPGCI	1.45590	0.2010
SPGCI does not Granger Cause BTC	2.22582	0.0492
OIL does not Granger Cause USDX	1.56108	0.1677
USDX does not Granger Cause OIL	0.88375	0.4910
MSCIE does not Granger Cause USDX	8.31443	8.E-08
USDX does not Granger Cause MSCIE	3.18812	0.0071
BTC does not Granger Cause USDX	1.46813	0.1969
USDX does not Granger Cause BTC	1.10287	0.3566
MSCIE does not Granger Cause OIL	2.64922	0.0214
OIL does not Granger Cause MSCIE	1.31359	0.2551
BTC does not Granger Cause OIL	1.14454	0.3344
OIL does not Granger Cause BTC	0.82430	0.5322
BTC does not Granger Cause MSCIE	1.50693	0.1842
MSCIE does not Granger Cause BTC	2.04382	0.0696

5. CONCLUSION

The results from the Granger causality tests and VAR analysis provide important insights into the interconnectedness of green bonds with major global financial and commodity markets. A key finding is the strong predictive influence of the Global Equity Index (MSCIE) on Green Bonds (SPGB), while green bonds themselves do not significantly influence other variables. This suggests that green bond performance is highly responsive to global equity market trends, which may reflect broader investor sentiment, macroeconomic conditions, and the availability of green investment capital that often correlates with bullish equity markets. Similarly, the bidirectional causality between MSCIE and the US Dollar Index (USDX) reflects the close interaction between global stock markets and currency movements, possibly driven by capital flows and interest rate expectations.

The lack of causality between green bonds and traditional assets like crude oil and Bitcoin could be due to their differing investor bases, time horizons, and risk-return characteristics. Green bonds are typically held by long-term, risk-averse institutional investors seeking stable returns and sustainability alignment, whereas oil and Bitcoin are more volatile, speculative assets. The non-significant causal influence of SPGB on commodities or Bitcoin reinforces the idea that green bonds may act more as followers rather than drivers in global asset dynamics.

The VAR results further support this interpretation by showing that green bonds are significantly influenced by their own lags and by global equity and currency movements, rather than exerting influence outward. Moreover, Bitcoin and crude oil exhibit minimal spillover effects into the green bond market, which aligns with their largely uncorrelated fundamentals and market structures. Overall, the findings highlight that green bonds are more reactive than influential in the global financial system, possibly due to their relatively newer status, lower liquidity, and the niche nature of ESG investing compared to conventional asset classes.

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