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EXPLORING THE LINKAGES BETWEEN GREEN BONDS AND INTERNATIONAL FINANCIAL MARKETS: AN INTERNATIONAL PORTFOLIO PERSPECTIVE

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ABSTRACT

The aim of study is to examine the dynamic linkages between green bond & international financial markets. In particular, the study investigates the inter-connections among green bonds, world's developed and emerging equity markets, commodities market (gold & oil) and the foreign exchange market. Sample period ranges from July 1, 2014, to June 30, 2023 encircling numerous important events including COVID-19 pandemics. For empirical investigation, study used combination of several econometric techniques including Johansen Cointegration model and Granger Causality test and analysis for examining short & for long-term associations among markets. Results of study show that these markets are linked in varying degrees in long-run as evident from cointegration results that show two cointegrating vectors. This infers that there are limited diversification benefits specially in long-run in selected markets. In short-run, results show diversification potential as showed by results from Granger Causality tests. Results have important implications for investors & fund managers in making portfolio decisions, & policy makers in devising various strategies for risk mitigation during turbulent periods.

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INTRODUCTION

The green bonds are financial tools crafted to generate funding for the projects that promote the environmental sustainability geared towards alleviating the adverse effect of economic activities on climate (Gao, Guo & Wei, 2023). The escalating challenges of global warming and unfavorable climate changes that have spurred policymakers to prioritize the establishment of sustainable green economy. This involves seamlessly integrating financial markets with the broader economy through issuance of eco-friendly financial assets (Ejaz, 2021). Over the last decade, in sphere of sustainable finance, green bonds have emerged as one of most innovative and prominent choices. The proceeds generated from issuance of green bonds are vital in supporting actions aimed at addressing climate change, conserving the natural resources and environmental pollution prevention (Broad & Cheng, 2019). The green finance domains have significantly expanded due to widespread adoption of green bonds (Zhang, 2018). It provides the clues towards future market size, potential impact on global financial stability, and long-term benefits for sustainable development. The green bonds along with associated commodities have evolved into a firmly established and sustainable investment option & prospects that is gaining traction among those who are increasingly recognizing substantial impact of climate change upon government policies and associated risks for businesses in diverse situations (Reboredo, 2018).

The green bonds provide potential avenues for risk mitigation and portfolio diversification, meeting investors' dual requirements of environmental stewardship and financial viability (Huynh, Hille & Muhammad, 2020). As shown by Maltais and Nykvist, (2020) the green bond emerged as a leading financial instrument for raising funds, is particular in shaping the continued expansion of the global green bond market contributes to fostering the low-carbon and resilient economy (Banga, 2019). Especially, stock exchanges have recently introduced dedicated segments for the green bonds, most important toward substantial expansion in green bond market size and significance, attracting both institutional and individual investors (Reboredo & Ugolini, 2020; Tang & Zhang, 2020). In pursuit of assessing volatility, several studies in the area of green investment have been conducted to model and identify presence of unpredictability spillover in green bond market & other financial markets, are subject to scrutiny (Wang, Liu, Li & Ramona, 2022). It offers the comparison with conventional bonds in terms of risk profile and returns. It further helps in providing the clues about role of green bonds in promoting sustainable finance, their impact on market dynamics, and their influence upon the investor behavior.

This transition unlocks new financial prospects for green bond issuers and investors while investors gain insights into environmental investment impacts for portfolio optimization. These bonds not only offer means of financing initiatives aimed at addressing climate change along with environmental challenges but also align with ESG-focused strategies that increasing the number of investors in the developed markets prioritize (Buckley, Rüdiger & Thierfelder, 2019). It provides the details about growth potential, technological advancements, and increasing investor awareness. Thus, given its unpredictability, green bond market intertwined is with various other economic markets. Therefore, investors employ green bonds to generate favorable returns on their investments while assisting to development of an economy resilient toward climate change (Huynh et al, 2020). It helps to address climate change, promoting sustainable growth & meeting ESG (Environmental, Social, Governance) criteria. This study examines relationships across many markets including green bonds and diverse global financial markets, including crude oil, gold, developed stock markets, US equity market, alongside emerging equity markets, and exchange rates. The aim is to offer investors with valuable information for predicting future returns, constructing well-balanced portfolios & maximizing their investment returns.

LITERATURE REVIEW

The emergence of the green market around 2007, there has been an increasing amount of literature exploring connections among green bonds and various financial and commodities markets. When examining the underlying relationships between green bonds and financial instrument, traditional commodities & environmental assets, results have been somewhat contradictory. Interestingly, Lee, Lee and Li (2021) found stock market, renewable energy, and green bonds depended dynamically on their tails rather than their static averages. Reboredo, (2018) utilizing bivariate copula models, study examined the interrelationships among stock and energy commodity markets, and markets for corporate and treasury bonds, studies considered markets for green bonds and many other fixed income securities. The findings revealed that green bonds had marginal connections with energy, stocks and commodity markets. Moreover, Choi and Hammoudeh, (2010) posits argument that price fluctuations in commodity assets should be routinely monitor by portfolio investors to improve the selection of portfolio. Ferrer, Shahzad and Soriano (2021) examined multi-scale spillovers between green bonds, financial markets, by utilizing frequency spillover index, Baruník and Křehlík, (2018) investigated interrelations in energy markets, financial markets, and green bond markets, revealing robust short-term links.

The results showed positive time varying and tail dependencies. Taghizadeh, Yoshino and Phoumin (2021) argued that the turn-down in prices of the oil may decrease the inspiration for advancement of the renewable energy, consequently negatively impacting growth of green bonds. Huang, Cao and Zhong (2022) argue that green bonds display a negative correlation with crude oil. Li, Zhou, Hu and Guo (2022) suggested that fluctuations in price of crude oil adversely impact the index of green bond. Deus, Crocco and Silva (2022) stressed that green bond market in China's gains from robust green policies, mitigating impact of outside upset including volatility in oil prices & fostering a shift toward sustainability. Umar, Ji, Kirikkaleli and Alola (2021) identified strong co-movements between green bonds and traditional bonds while limited correlation with conventional stocks and commodities. Le et al. (2021) revealed that volatility was transmitted largely across many markets in short terms, with green bonds subjected to net volatility shocks. Huynh et al. (2020) explored that portfolio composed of these assets exhibited notable reliance on heavy tails, suggesting heightened probability of extensive joint losses during periods of economic instability. Short-term transmissions of volatility were pronounced compared to long-term transmission, with bitcoin and gold identified as crucial hedging assets.

Azhgaliyeva et al. (2021) showed that oil supply shocks positively influenced green bond issuance, contrary to overall market trend. Henriques and Sadorsky, (2008) found significant impact of oil price shocks on alternative energy stock prices. However, it did uncover those shocks to stock prices technology had noteworthy positive effect on the energy stock prices alternative (Sadorsky, 2012). Mensi et al. (2021) revealed evidence of asymmetric spillovers within green bond market. Explicitly, evidence suggested that green bonds exhibition faces of an asset distinct class, connected closely to currency exchange rates and treasury bonds, while presenting diversification benefits, compared to other asset types. In this connection, this may pique interest investors in green bonds and encourage potentially increased investment flows toward low-carbon projects, by this means providing issuers with chance to expand their long-term investor green base. A limited number of prior studies have examined the inter-relationship between green bonds and international financial markets, such as commodity market, equity market, and exchange market. First, this study investigates both short-term and long-term dynamic connections among the most important global financial markets in the conjunction with green bond market. Secondly, study investigated a more recent period encircling the recent health crisis due to COVID-19 pandemics. Thirdly, a combination of various econometric techniques has been used for investigation to identify the potential assets having safe-haven and hedging capabilities.

RESEARCH METHODOLOGY

The time series data is extracted from the website of investing.com for this study. The daily closing prices of green bond (GB), Crude Oil prices (CO), Gold prices (GD), Developed Stock markets (DM), U.S Stock Market (USM), Emerging Stock market (EM) and Exchange Rate (ER) is taken from period July 1st, 2014 to June 30th, 2023 there by providing the sample size of (2374) observations. This sample period covers recent data for these markets. The rate of return can be calculated by using the formula:

$$\boldsymbol{R_t = \ln(P_t / P_{t-1})} \quad \text{(i)}$$

Where, R_t = return on day: t ln=natural log, P_t=closing price on day t, P_{t-1} = closing price on day t-1

To investigates inter-relationship among selected variables thereby using the descriptive statistics, correlation matrix, unit root test, Johansen Co-integration test, Granger Causality test. Descriptive statistics reports basic features of data and correlation matrix identifies presence of co-movement among variables of study. Unit root test is applied for checking stationarity of data. For applying co-integration test the series should be non-stationary but should be integrated of order one I (1). Thus, to check whether all series are integrated of order one unit root tests were used. Most common used test is Augmented Dickey Fuller (ADF) and Phillip Perron (PP) test. The models of ADF and PP test are given below:

Augmented Dickey Fuller (ADF)

$$\boldsymbol{\Delta x_t = \alpha_0 + \beta t + \gamma x_{t-1} + \sum_{i=1}^{n} \delta i \, \Delta x_{t-i} + \varepsilon_t} \quad \text{(ii)}$$

Where:

t = Represents the time index, x_t = Denotes the variable in period "t", α◦ = Stands for the intercept constant referred to as the drift, β = Represents the coefficient on the time trend, γ = Symbolizes the coefficient presenting the process root, δ = Represents the lag order of first difference, ε_t = Signifies an independent identically distributed residual term. Thus, Phillip-Perron (P-P) test is represented as follows;

$$\boldsymbol{y_t = \beta_\circ + \beta_1 y_{t-1} + \beta_2 (t - T/2) + \varepsilon_t} \quad \text{(iii)}$$

Where:

y_t= Represents variable in time period "t", β◦= Denotes intercept, β_1&β_2= Stand for coefficients, T= Represents number of observations, ε_t= Signifies disturbance term. The series is non-stationary is the null hypothesis of both ADF test and PP test.

Where: Ho: $\emptyset = 0, \ \ \rho = 1$ and H1: $\emptyset < 1, \rho < 1$

Johansen Co-integration Test is applied to check inter-relationship among selected variables. The study utilizes Johansen co-integration method (1988) to examine correlation among the variables over the long term. Johansen co-integration test initiates with Vector Auto-regression (VAR) model. Thus, VAR can be formulated as:

$$\mathbf{X_t = A_1X_{t-1} + A_2X_{t-2} + \cdots + A_iX_{t-i} + \varepsilon_t} \quad \text{(iv)}$$

It can be rewrite as:

$$\mathbf{\Delta x_t = \Pi x_{t-1} + \Sigma\Gamma\Delta x_{t-i} + \varepsilon_t} \quad \text{(v)}$$

Where:

$\Pi = \Sigma A_i - I$

$\Gamma_i = -\Sigma A_i$

The matrix Π has the rank (r) by which it determines the presence of the co-integrating vectors. To estimate VAR, it is necessary to select optimal lag length and for that purpose the criteria of Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) have been used in study. In this connection, Johansen Co-integration test is based on two likelihood ratio tests one is Trace test and given as:

$$\boldsymbol{\lambda_{trace}(r) = -T\sum_{i=r+1}^{n} \mathrm{In}\,(1-\lambda_i)} \quad \text{(vi)}$$

Where:

r =number of co-integrating vectors, ln=natural log, λ_i =estimated value for ith ordered eigenvalue

Where the null hypothesis is;

Ho: number of cointegration vector $\leq$ r

Other test is Maximum Eigen value test that can be expressed as:

$$\boldsymbol{\lambda_{max}(\mathbf{r}, \mathbf{r}+1) = -\mathbf{T}\mathrm{\mathbf{ln}}\,(1-\lambda_{r+1})} \quad \text{(vii)}$$

Where Ho: number of cointegration relationship = r

Granger Causality Test is used to explore existence of short-run causal relationship amid variables. The general equations used are given below:

$$\boldsymbol{Y_t = \sum \alpha_i X_{t-i} + \sum \beta_j Y_{t-j} + \varepsilon_{1t}} \quad \text{(viii)}$$

$$\mathbf{X_t = \sum \lambda_i X_{t-i} + \sum \delta_j Y_{t-j} + \varepsilon_{2t}} \quad \text{(ix)}$$

Where:

$\mathbf{Y_t}$ and $\mathbf{X_t}$ = stationary variables

$\boldsymbol{\varepsilon_{1t}}$ and $\boldsymbol{\varepsilon_{2t}}$ = uncorrelated white noises series

RESULTS OF STUDY

Table 1 provides a summary of the statistical characteristics of the data, including measures such as mean, median, SD, skewness, kurtosis, and Jarque-Bera test. Table 1 presents descriptive statistics for the variables:

Table 1 Descriptive statistics

	GB	CO	GD	DM	USM	EM	ER
Mean	0.0004	0.0003	0.0002	0.0001	0.0003	-0.0001	-0.0001
Median	0.0005	0.0013	0.0002	0.0008	0.0006	0.0004	-0.0001
Maximum	0.0867	0.5417	0.0578	0.0796	0.0897	0.0775	0.0302

Minimum	-0.1159	-0.2822	-0.0511	-0.1218	-0.1277	-0.1333	-0.0242
Std. Dev.	0.0114	0.0319	0.0092	0.0114	0.0115	0.0133	0.0051
Skewness	-0.7976	2.1334	-0.0305	-2.7982	-0.8406	-0.7162	0.1083
Kurtosis	16.4012	53.0867	7.0085	31.1610	18.5406	11.7956	5.2232
Jarque-Bera	18016.5*	249951*	1589.73*	81543.5*	24169.0*	7855.53*	493.54*
Observations	2374	2374	2374	2374	2374	2374	2374

Note: Table 1 show descriptive statistics of the selected variables from 3 1st July, 2014 to 30th June, 2023. The (*) denotes values that are significant at the 5 percent significance level.

The table 1 shows return and standard deviation of each variable. GB gives 0.0004 percent return with the risk level 0.0114 percent. CO gives 0.0003 percent return with risk level 0.0319 percent. GD, DM, USM, EM and ER give 0.0002 percent, 0.0001%, 0.0003 percent, -0.0001 and -0.0001 percent with risk level 0.0092 percent from GD, 0.0114 percent from DM, 0.0115 percent from USM, 0.0133 percent from EM and 0.0051 percent from ER. When comparing mean returns with standard deviation, the investor can assess risk-adjusted performance of each variable. A higher mean return is desirable, but not at cost of extremely high volatility. A higher standard deviation indicates greater risk and uncertainty. Table 1 shows that variable "CO" has mean return of 0.0003 and a standard deviation of 0.0319. "ER" has a mean return of -0.0001 and a SD of 0.0051. Comparing these two variables, "ER" has a lower mean return but a lower SD, which means it offers a more stable and less risky return as compared to "CO." The maximum and minimum show the largest and smallest value in our data set to calculate range.

The maximum value of CO is reported 0.5417, which is largest value in our data set. The minimum value of GD is reported -0.0511, which is the smallest value in our data set. The Skewness shows that distribution is asymmetric. Table 1 exhibits the results of skewness that show distribution of GB, GD, DM, USM and EM are negatively skewed. And it indicates that the distribution is skewed to the left. It means that this variable has lower return. While CO, ER are positive skewed and it indicates a right-skewed distribution. It means that the variables have higher return. In table 1 kurtosis show trends in the data and the distribution of data around the mean. The kurtosis of normal distribution is 3. Kurtosis of GB is 16.4012 and that is leptokurtic that the means distribution is more clustered around the mean and there is less variation in the observation. CO, GD, DM, USM, EM and ER have the kurtosis of 53.0867, 7.0085, 31.1610, 18.5406, 11.7956 and 5.2232 and show leptokurtic. Jarque-Bera statistic confirms the result of skewness and kurtosis indicates that the data exhibits abnormal distribution characteristics. Additionally, all the Jarque-Bera statistics values are significant at 5% level of significance.

Table 2 Correlation Matrix

	GB	CO	GD	DM	USM	EM	ER
GB	1						
CO	0.02	1					
GD	0.01	-0.02	1				
DM	0.27	-0.02	0.04	1			
USM	0.32	-0.01	0.02	0.20	1		
EM	0.15	0.02	0.04	0.14	0.13	1	

ER	-0.01	0.05	0.11	0.03	-0.03	0.05	1

Note: Table 2 represents the values of correlation coefficients among selected variables from 2014-2023.

Table 2 shows the degree of correlation between variables. The correlation co-efficient of GB and USM is 0.32 that show higher positive correlation than correlation between other variables. There is lowest correlation between GD and GB and USM and CO, ER and GB with correlation coefficient of 0.01; but their negative correlation between USM and CO as well as ER and GB means that increase in the return of one sector will cause decrease in another sector. The pair wise correlation between CO and GB as well as EM and CO as well as USM and GD and GD and CO, DM and CO are 0.02; but their negative correlation amid GD and CO and DM and CO. The pair wise correlation between ER CO and ER and EM is 0.05. The pair wise correlation between DM and GD and EM and GD are 0.04. The pair wise correlation amid ER and DM and ER and USM is 0.03; but there is negative correlation amid ER and USM.

The pair wise correlation between DM and GB (0.27), EM and GB (0.15), ER and GD (0.11), USM and DM (0.20), EM and DM (0.14), EM and USM (0.13). So, results found that USM and GB are highly correlated variables. Thus, it can be hypothesized that they will be integrated in the long-run as well as in the short-run. There is less chance of diversification gain by investing in USM and GB. The unit root test is utilized to ascertain the stationarity of the data. Prior to employing the co-integration method, it is imperative to confirm whether time series are integrated of order one, denoted as I (1), indicating stationarity at the first difference level. In this connection, the Augmented Dickey Fuller (ADF) and Phillip Perron (PP) tests are commonly utilized for this purpose. In this study, both the ADF and PP tests were conducted in this study at the level and first difference. In this regard, table 3 presents the outcomes of these tests.

Table 3 Unit Root Test

Variables	Augmented Dickey Fuller Test		Phillip Perron Test	
	Level T-Stat	1st Diff T-Stat	Level Adj.T-Stat	1st Diff Adj.T-Stat
GB	-0.59	-15.34*	-0.52	-53.40*
CO	-2.25	-41.36*	-2.29	-63.35*
GD	-0.67	-50.06*	-056	-50.18*
DM	-2.71	-51.79*	-2.14	-51.70*
USM	-0.57	-15.42*	-0.49	-54.25*
EM	-2.12	-52.51*	-2.16	-52.52*
ER	-2.49	-49.36*	-2.46	-49.49*

Table 3 shows the results of ADF (Augmented Dickey Fuller) and PP (Phillip Perron) test. The table exhibit the value of t-statistics. * Indicates the rejection of null hypothesis at 5 percent significance level.

In table 3 both ADF and PP test found that all the series have unit root at the level but become stationary at first difference. By analyzing the results, it is noted that at level the values of t-statistic of all the series are less than 2.86, which is critical value at 5 percent significance level, while at first difference these t-statistic values become higher than 2.86. This causes the rejection of the null hypothesis of non-stationarity and all the series becomes stationary at first difference. As the results concluded that all the series are integrated of order one i-e I (1), so the study can use co-integration models for analysis. In this regard, this paper applied Johansen co-integration to investigate the long-run association among selected variables. The table 4 and 5 showed these tests as evident from the results in table.

Table 4 Trace Test

Hypothesized		Trace	0.05	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.12	425.76	125.62	0.00
At most 1 *	0.02	128.65	95.75	0.00
At most 2	0.01	74.71	69.82	0.11
At most 3	0.01	43.68	47.86	0.12
At most 4	0.01	23.37	29.79	0.22
At most 5	0.00	7.66	15.49	0.50
At most 6	0.00	0.00	3.84	0.97

Notes: Table shows the results of Trace test that specify 2 co-integrating equation at 5 percent significance level. * Denotes rejection of the null hypothesis at the 5percent level of significance. ** p- values.

Table 5 Maximum Eigen value Test

Hypothesized		Max-Eigen	0.05	
No. of CE(s)	Eigen value	Statistic	Critical Value	Prob.**
None *	0.12	297.10	46.23	0.00
At most 1 *	0.02	53.95	40.08	0.00
At most 2	0.01	31.03	33.88	0.11
At most 3	0.01	20.30	27.58	0.32
At most 4	0.01	15.71	21.13	0.24
At most 5	0.00	7.66	14.26	0.41
At most 6	0.00	0.00	3.84	0.97

Notes: Table shows results of Max-eigenvalue test specify 2 co-integrating equation at 5% significance level. * Denotes rejection of the null hypothesis at the 5 percent level of significance. ** p- values

In tables 4 and 5 Trace test and Maximum Eigen value reveals the evidence of two co-integration vectors at 5 percent level. The result indicates that there is no diversification benefit for investors in long-run because of presence of long-run relationship in selected markets in diverse circumstances. Further to investigate short-run association between variables GC test is applied. This test may show either unidirectional causal relationship or bidirectional lead lag association. Table 6 represents result of Granger Causality.

Table 6 Granger causality Test for the Variables over the Period 2014 to 2023

Null Hypothesis:	N	F-Statistic	Prob.
CO to GB	2374	8.01	0.00*
GB to CO		2.60	0.01*
GD to GB	2374	3.01	0.00*

GB to GD		1.77	0.10
DM to GB	2374	1.07	0.38
GB to DM		0.91	0.50
USM to GB	2374	4.75	0.01*
GB to USM		166.04	0.00*
EM to GB	2374	1.47	0.16
GB to EM		0.68	0.71

Table 6A Granger causality Test for the Variables over the Period 2014 to 2023

Null Hypothesis:	N	F-Statistic	Prob.
ER to GB	2374	2.69	0.00*
GB to ER		3.58	0.00*
GD to CO	2374	4.69	0.00*
CO to GD		3.14	0.00*
DM to CO	2374	2.12	0.03*
CO to DM		2.77	0.00*
USM to CO	2374	1.37	0.20
CO to USM		3.95	0.00*
EM to CO	2374	2.77	0.00*
CO to EM		2.14	0.02*
ER to CO	2374	1.54	0.13
CO to ER		1.16	0.31
DM to GD	2374	1.81	0.10
GD to DM		2.68	0.01*
USM to GD	2374	1.03	0.41
GD to USM		3.12	0.00*

Table 6B Granger causality Test for the Variables over the Period 2014 to 2023

Null Hypothesis:	N	F-Statistic	Prob.
EM to GD	2374	1.61	0.11
GD to EM		1.74	0.10
ER to GD	2374	0.77	0.63
GD to ER		1.40	0.19
USM to DM	2374	1.07	0.43
DM to USM		3.17	0.00*
EM to DM	2374	38.36	0.00*
DM to EM		2.47	0.01*
ER to DM	2374	1.51	0.15
DM to ER		1.55	0.13
EM to USM	2374	1.35	0.22
USM to EM		0.76	0.64
ER to USM	2374	2.01	0.04*
USM to ER		2.38	0.02*
ER to EM	2374	0.64	0.75
EM to ER		1.99	0.04*

Note: Table 6 represents causal relationship between green bond and international financial markets. *Shows rejection of null hypothesis at 5 percent significance value. N represents the number of observations

Table 6 shows results of Granger Causality test that represent that there Eight bidirectional lead and lag relationship exist between GD and CO, USM and GB, ER and GB, GD and CO, DM and CO, EM and CO, EM to DM and ER to USM. Results represent six unidirectional causal relationships where flow of causal relation is from GD to GB, CO to USM, GD to DM, GD to USM, DM to USM and EM to ER. GB does not cause GD, DM and EM; CO does not cause ER; GD does not cause EM and ER; DM does not cause GB, GD and ER; USM does not cause CO, GD, DM and EM; EM does not cause GB, GD and USM; ER does not cause CO, GD, DM and EM.

DISCUSSION & CONCLUSION

To achieve desired objectives, the study examines the daily returns of international green bonds and international stock markets (developed stock market, U.S Stock market and emerging stock market) international commodity market (oil market and gold market) and international exchange markets. Sample period from July 2014 to June 2023 is utilized for the analysis. The unit root test indicates that all series are non-stationary at the level but stationary at first difference, suggesting they are integrated of order one (I (1)). The Johansen Co-integration test is then applied to examine long-run relationship among sectors, requiring non-stationary data integrated at the same order. As per the unit root test results, the data meets the prerequisites for Johansen Co-integration test. In this connection, this test, based on Trace test and Maximum Eigenvalue test, identifies two co-integrating equations at a 5 percent significance level. Consequently, these findings indicated that the markets were inter-connected in the long-run providing limited benefits from diversifications into these markets.

To highlight the directional causal relationship among the markets, the Granger Causality test is employed to discern the short-run unidirectional causal relationships or the bidirectional lead-lag relationships. The results indicated the presence of the eight bidirectional lead and lag relationship exist between GD and CO, USM and GB, ER and GB, GD and CO, DM and CO, EM and CO, EM to DM and ER to USM. The results represent six unidirectional causal relationships where the flow of causal relation is from GD to GB, CO to USM, GD to DM, GD to USM, DM to USM and EM to ER. GB does not cause GD, DM and EM; CO does not cause ER; GD does not cause EM and ER; DM does not cause GB, GD and ER; USM does not cause CO, GD, DM and EM; EM does not cause GB, GD and USM; ER does not cause CO, GD, DM and EM. These findings indicated a weaker connection between the green bond and commodities markets, indicating the potential diversification benefits from investing in these markets. Moreover, gold and oil markets showed safe-haven and hedging capabilities being more isolated in the system.

Based on risk tolerance and investment goals, investors can tailor their portfolio to include riskier assets for higher returns or safer assets for capital preservation. The results show that different assets have varying levels of risk rather to invest in selected markets. It shows that their limited change benefits in selected markets. So, study suggested that investor diversify risk by investing in other markets. For balance portfolio the investor needs to allocate their investment in the assets like gold, crypto currency. There are numbers of other financial markets and have greater impact but this study investigates four selected markets & cannot investigate all those other markets. Study relies on historical data and used sample period July 2014 to June 2023. There are number of financial tools used to examine relationship, volatility dynamics, market risk, co-movements diversification. So, in future researcher can find linkages among those markets by selecting sample period onward 2023 with different techniques.

REFERENCES

Azhgaliyeva, D., Mishra, R., & Kapsalyamova, Z. (2021). Oil price shocks and green bonds: A longitudinal multilevel model (No. 1278).

Banga, J. (2019). The green bond market: a potential source of climate finance for developing countries. *Journal of Sustainable Finance Investment*, 9 (1), 17–32.

Baruník, J., & Křehlík, T. (2018). Measuring frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, 16(2), 271-296.

Broad stock, D. C., & Cheng, L. T. (2019). Time-varying relation between black and green bond price benchmarks: Macroeconomic determinants for first decade. *Finance Research Letters*, 29, 17–22.

Buckley, R. P., Rüdiger, F., & Thierfelder, C. (2019). The Global Green Finance Index 4. Z/Yen Group. Retrieved from https://www.longfinance.net/images/GGFI_4.pdf.

Choi, K., & Hammoudeh, S. (2010). Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. *Energy policy*, 38(8), 4388-4399.

Deus, J. L., Crocco, M., & Silva, F. F. (2022). The green transition in emerging economies: green bond issuance in Brazil and China. *Climate Policy*, 22(9-10), 1252-1265.

Ejaz, R. (2021). Green Bond and International Financial Markets: Spillover, Co-movement and Diversification (Doctoral Dissertation, Capital University).

Ferrer, R., Shahzad, S. J. H., & Soriano, P. (2021). Are green bonds a different asset class? Evidence from time-frequency connectedness analysis. *Journal of Cleaner Production*, 292, 125988.

Gao, L., Guo, K., & Wei, X. (2023). Dynamic relationship between green bonds and major financial asset markets from the perspective of climate change. *Frontiers in Environmental Sciences*. 10:1109796.

Henriques, I., & P. Sadorsky. (2008). Oil Prices and Stock Prices of Alternative Energy Companies. *Energy Economics*, 30 (3), 998–1010.

Huang, J., Cao, Y., & Zhong, P. (2022). Searching for a safe haven to crude oil: Green bond or precious metals? *Finance Research Letters*, 50, 103303.

Huynh, T. L D., Hille, E., & Muhammad, A. N. (2020). Diversification in the age of the 4th industrial revolution: The role of artificial intelligence, green bonds & crypto currencies. *Technological Forecasting and Social Change*, 159, 120188.

Huynh, T. L. D. (2020). The effect of uncertainty on the precious metals market: New insights from Transfer Entropy and Neural Network VAR. *Resources Policy*, 66, 101623.

Le, T. L., Abakah, E. J. A., & Tiwari, A. K. (2021). Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution. *Technological Forecasting and Social Change*, 162, 120382.

Lee, C. C., Lee, C. C., & Li, Y. Y. (2021). Oil price shocks, geopolitical risks, and green bond market dynamics. *The North American Journal of Economics and Finance*, 55, 101309.

Li, H., Zhou, D., Hu, J., & Guo, L. (2022). Dynamic linkages among oil price, green bond, carbon market and low-carbon footprint company stock price: Evidence from the TVP-VAR model. *Energy Reports*, 8, 11249-11258.

Maltais, A., & Nykvist, B. (2020). Understanding the role of green bonds in advancing sustainability. *Journal of Sustainable Finance and Investment*. 20 (1), 271-296

Mensi, W., Hernandez, J. A., Yoon, S. M., Vo, X. V., & Kang, S. H. (2021). Spillovers and connectedness between major precious metals and major currency markets: The role of frequency factor. *International Review of Financial Analysis*, 74, 101672.

Reboredo, J. C. & Ugolini, A. (2020). Price connectedness between green bond and financial markets. *Economic Modelling*, 88,25–38.

Reboredo, J. C. (2018). Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energy Economics*, 74, 38–50.

Sadorsky, P. (2012b). Correlations and Volatility Spillovers between Oil Prices and the Stock Prices of Clean Energy and Technology Companies. *Energy Economics*, 34 (1), 248–55.

Taghizadeh, F., Yoshino, N., & Phoumin, H. (2021). Analyzing the characteristics of green bond markets to facilitate green finance in the post-COVID-19 world. *Sustainability*, 13(10), 5719.

Tang, D. Y., & Zhang, Y. (2020). Do shareholders benefit from green bonds? *Journal of Corporate Finance*, 61, 1–18.

Umar, M., Ji, X., Kirikkaleli, D., & Alola, A. A. (2021). The imperativeness of environmental quality in the United States transportation sector amidst biomass-fossil energy consumption and growth. *Journal of Cleaner Production*, 285, 124863.

Wang, K. H., Liu, L., Li, X., & Ramona, L. (2022). Do oil price shocks drive unemployment? Evidence from Russia and Canada. *Energy*, 253, 124107.

Zhang, D. (2018). Energy finance: Background, concept, & recent developments. *Emerging Markets Finance and Trade*, 54(8), 1687–1692.