A cross-quantile correlation and causality-in-quantile analysis on the relationship between green investments and energy commodities during the COVID-19 pandemic period

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Abstract

Purpose: This paper aims to examine the cross-quantile correlation and causality-in-quantiles between green investments and energy commodities during the outbreak of COVID-19. To be specific, we aim to address the following questions: (1) Is there any distributional predictability among green bonds and energy commodities during COVID-19? (2) Is there exist any directional predictability between green investments and energy commodities during the global pandemic? (3) Can green bonds hedge the risk of energy commodities during a period of the financial crisis.

Methodology: We use the nonparametric causality in quantile and cross-quantilogram correlation approaches as the estimation techniques to investigate the distributional and directional predictability between green investments and energy commodities respectively using daily spot

prices from January 1, 2020, to March 26, 2021. The study uses daily closing price indices S&P Green Bond Index as a representative of the green bond market. In the case of energy commodities, we use S&P GSCI Natural Gas Spot, S&P GSCI Biofuel Spot, S&P GSCI Unleaded Gasoline Spot, S&P GSCI Gas Oil Spot, S&P GSCI Brent Crude Spot, S&P GSCI WTI, OPEC Oil Basket Price, Crude Oil Oman, Crude Oil Dubai Cash, S&P GSCI Heating Oil Spot, S&P Global Clean Energy, US Gulf Coast Kerosene and Los Angeles Low Sulfur CARB Diesel Spot.

Findings: From the cross-quantilogram correlation results, there exists an overall negative directional predictability between green bonds and natural gas. We find that the directional predictability between green bonds and S&P GSCI Biofuel Spot , S&P GSCI Gas Oil Spot, S&P GSCI Brent Crude Spot, S&P GSCI WTI Spot, OPEC Oil Basket Spot , Crude Oil Oman Spot , Crude Oil Dubai Cash Spot, S&P GSCI Heating Oil Spot, US Gulf Coast Kerosene-Type Jet Fuel Spot Price and Los Angeles Low Sulfur CARB Diesel Spot Price is negative during normal market conditions and positive during extreme market conditions. Results from the non-parametric causality in the quantile approach show strong evidence of asymmetry in causality across quantiles and strong variations across markets.

Originality: Our paper differs from these previous studies in several aspects. First, we have included a wide range of energy commodities comprising 3 green bond indices and 14 energy commodities indices. Second, we have explored the dependency between the two markets, particularly during COVID-19 pandemic. Third, we have applied cross-quantilogram and causality-in-quantile methods on the given dataset. Since the market of green and sustainable finance is growing drastically and the world is transmitting towards environment-friendly practices. It becomes vital to understand the impact of green bonds on other financial markets. In this regard, the study contributes to the literature by documenting an in-depth connectedness between green bonds and crude oil, natural gas, petrol, kerosene, diesel, crude, heating oil, biofuels, and other energy commodities.

Practical implications: The quantile time-varying dependence and predictability results documented in this paper can help market participants with different investment targets and horizons adopt better hedging strategies and portfolio diversification to aid optimal policy measures during volatile market conditions.

Social implications: The outcome of this study will promote awareness regarding the environment and also increase investor`s participation in the green bond market. Further, it allows corporate institutions to fulfill their social commitment through the issuance of green bonds.

Key Words: Green bond, energy commodity markets, quantile dependence, quantile predictability.

JEL Classification: G11, Q02, Q41, Q43

1. Introduction

In the wake of environmental awareness, sustainability, and clean energy, the concept of green bonds was introduced European Investment Bank (EIB) in 2007. The largest green bond till date was endowed by the Republic of France amounting to EUR 7 billion (Gianfrate & Peri, 2019). Green bonds are defined as any class of bonds which uses the funds of its proceeds for eligible green projects like reduction in green gas emissions, pollution control, management of waste and water, environmental conservation, renewable energy, energy, and resource efficiency (Gianfrate & Peri, 2019). The mantle of these bonds is that they help in driving the capital towards more sustainable economic activities. Similar to conventional bonds, these bonds are issued by the third party which includes municipalities, corporates, and other government entities to finance or refinance green projects. The environmentally friendly nature of these bonds has made them singularly voguish, which has led to what is referred to as the "green bond boom". As per Liu et al. (2021), the issuance of green bonds has a positive impact on the clean energy sector, since the green bonds market can fulfill the funding requirement of firms operating in the clean energy sector. However, there is no direct impact on the company`s operating efficiency due to the issuance of green bonds (Yeow & Ng, 2021).

On the contrary conventional energy market such as crude oil is negatively impacted by the issuance of green bonds (Lee et al., 2020), since green bonds aim at minimizing the use of fossil fuels and thereby limit their harmful environmental consequences. Energy commodities being a sally in the production of goods and services plays a pivotal role in the economy, and global financial market. Therefore, they have a substantial impact on the financial market, business cycle fluctuations and the economy as a whole. Prices of crude oil have a significant impact on the transportation, production, and manufacturing of goods and services; therefore, it is referred to as the lifeblood of industries (Meng et al., 2020). Consequently, their prices impact the financial market and the overall economy (He et al., 2012). Just like crude oil, natural gas is another vital component in production, and is pompously affected by any demand shocks in the economy (Driesprong et al., 2008). However, a proper substitute of renewable energy can help to consummate the demand for conventional energy products apart from aiding in the accomplishment of sustainable development goals.

Various studies have explained the co-movement between the green bond market and different asset classes (Hachenberg & Schiereck, 2018; Huynh et al., 2020; Reboredo et al., 2020; Liu et al., 2021). Roy (2015), Reboredo (2018), and Pham (2021) have explained the relationship between green bonds and various classes of financial assets. Various researchers have explored the dependency structure between green bonds and the commodity markets (Nguyen et al., 2020; Naeem et al., 2021; Le et al., 2021). Nguyen et al. (2020) used a wavelet approach to study the connection between green bonds, and different financial assets namely renewable energy, conventional bonds and equity. Naeem et al. (2021) applied a cross-quantilogram approach to study the diversification benefits of adding green bonds to the portfolio. Liu et al. (2021) find coherence between clean energy and green bonds.

According to many authors, the connectedness between green bonds and other financial market have intensified during the period of a financial crisis (Naeem et al,2020; Arif et al, 2022; Pham & Nguyen, 2022), mainly due to the safe-haven and diversification properties of green bonds (Arif et al., 2022). The outbreak and rapid spread of COVID-19 in December 2019 has heightened uncertainty in the global financial market (Benigno et al., 2020; OECD, 2020. Stock markets of Germany, France, and Italy had plunged in their market values. National lockdown and movement restrictions which led to the closures of manufacturing, transportation, and non-essential businesses greatly impacted the economic health of many countries across the globe. Eventually, this resulted in a crash in the oil market. Prices of crude oil had plunged to $ 20 per barrel (Arif et al., 2021). As a consequence of it, investors drove their savings from stocks and commodities to safe-haven assets such as green bonds. Hence, this underscores the need to explore the impact of oil and other energy commodities on safe haven assets such as green bonds during COVID- 19 on a broader economy.

Interestingly, even though several studies on the effect of COVID-19 have emerged in the finance and economic literature, evidence on the effects of the COVID-19 outbreak on global markets remains scant. This study, therefore, fills this gap in the literature and contributes to studies that explore the financial effects of the COVID-19 pandemic by investigating the distributional and directional predictability between green bond markets and energy commodities including Natural Gas, Biofuel, Gasoline, Gas Oil, Brent Crude Oil, WTI Crude Oil, OPEC Oil, Crude Oil

Oman, Crude Oil Dubai Cash, Heating Oil, Clean Energy, US Gulf Coast Kerosene and Diesel. To be specific, we aim to address the following questions: (1) Is there any distributional predictability among green bonds and the above-mentioned energy commodities during COVID-19? (2) Is there exist any directional predictability between green investments and energy commodities during the global pandemic? (3) Can green bonds hedge the risk of energy commodities during a period of a financial crisis.

We apply the novel causality-in-quantile methodology by Balcilar et al. (2016) to investigate distributional predictability. Further, we also explore the directional predictability across the markets by utilizing the methodology by Han et al. (2016). These novel estimation techniques enable us to explore the quantile interdependencies across whole quantiles. Gemici & Polat,(2021), causality in mean and causality in variance to explain the relationship between Bitcoin, Litecoin & Ethereum for the period starting from August 7, 2015 to July 10, 2018. While Fousekis, & Grigoriadis, (2021) have applied cross-quantilogram to describe the return and volume of the cryptocurrencies from January 1, 2018 to June 30, 2020. In addition, instead of focusing on contemporary association as discussed elaborately in the prior literature, we focus on the predictive perspective.

We contribute to the emerging strand of literature that examines the causality and dependence between financial and green bond markets during the outbreak of the COVID-19 pandemic. In particular, our contribution is manyfold. We provide first-time empirical evidence on the predictability between green bonds and energy commodities under extreme market conditions and across different quantiles using robust estimation techniques. Second, this study is the foremost that uses the causality-in-quantile modeling technique to explore the distributional predictability of energy commodity returns and volatility using green bond prices during the period of the COVID-19 outbreak. Thus, based on the states of the markets, we provide empirical evidence on the impingement of green bond prices on energy commodities and vice versa during the COVID-19 period. The market conditions reflect the conditional quantiles following the approach of Bacilar et al. (2016)'s novel non-parametric causality in quantile test. The non-parametric causality-in-quantile technique is unique given that it is influenced by outlier observations. Additionally, it can also determine the Granger causality between markets under examination across the entire distribution. The non-parametric causality in the quantile approach takes care of the potential regime jumps and changes in the data (Dungey & Hvozdyk, 2012; Chevallier & Lelpo, 2014). Third, we also examine the causality-in-variance between green bond markets and energy commodity markets as a rejection of causality in the mean is not sufficient to predict the possibility of causality. Fourth, we use the cross-quantilogram (CQ) method by Han et al. (2016) to capture the asymmetries in the cross-quantile dependence structure. The benefit of the CQ methodology is that it considers the dependency nature amid extremes, unlike earlier estimations methods in the literature which are dependent on the distribution regions. We address this major research lacuna in the empirical literature by adopting a model of estimation which is free of estimation based on distribution. Lastly, this study establishes the magnitude of causality and direction of causality conditioned on the states of the markets which would be useful to policymakers who develop and implement strategies based on the market conditions.

We document several interesting findings. From the cross-quantilogram correlation results, we find the existence of overall negative directional predictability between green bonds and natural gas. While the directional predictability between green bonds and S&P GSCI Biofuel Spot , S&P GSCI Gas Oil Spot, S&P GSCI Brent Crude Spot, S&P GSCI WTI Spot, OPEC Oil Basket Spot, Crude Oil Oman Spot, Crude Oil Dubai Cash Spot, S&P GSCI Heating Oil Spot, US Gulf Coast Kerosene-Type Jet Fuel Spot Price, and Los Angeles Low Sulfur CARB Diesel Spot Price during normal market conditions.

While, in the case of extreme market conditions, the directional predictability of these commodities is positive with green bonds. This can be due to the fact that during the extreme market conditions, the state is under pressure to control prices and inflation. However, during bullish market conditions, the government has enough resources to develop a substitute for conventional energy such as crude oil, petroleum, and diesel, and thereby promote the clean energy market. Results from the non-parametric causality in the quantile approach show strong evidence of asymmetry in causality across quantiles and strong variations across markets. Results predominantly suggest to the investors that Los Angeles, Low Sulfur CARB Diesel Spot Price can obtain predictability in information during normal market conditions, when paired with green bonds. In bear regimes, there is no predictability in returns of the US Gulf Coast Kerosene and S&P Global Clean Energy with green bonds, this reflects the safe haven properties of green bonds against these commodities. The logical behind it could be that during a period of financial crisis, investors prefer of transform their portfolio towards fixed income assets like bonds and therefore there is an opposite price directional movement among green bonds and energy commodities (Rao et al, 2022). For S&P GSCI Petroleum Spot, Crude Oil Dubai Cash Spot, Crude Oil Oman Spot, OPEC Oil Basket Spot, and S&P GSCI WTI Spot, the predictability is strong at the tails than at the median, thereby indicating the inability of green bonds to hedge the risk of these commodities.

The paper henceforth advances as follows: section 2 provides a brief review of the extant literature. The methodology is described in Section 3. Data sets and descriptive statistics are discussed in section 4. The empirical discussion is presented in Section 5. Finally, Section 6 gives the concluding remarks.

2. Literature Review

In the past few years, there is a spontaneous expansion in green finance markets, particularly green bonds. First, it deserves to mention that a significant part of the relative literature has explained the concept of green bonds, its advantages, and performance (see for instance, Gianfrate & Peri ,2019; Flammer, 2020; Zerbib,2019; Kanamura, 2020; Tang & Zhang, 2020). More precisely, Gianfrate & Peri (2019) and Flammer (2020) emphasized the environmental benefits of green bonds and how the issuance of these bonds can help to attain sustainable goals in the long run. Li et al (2020), mentioned the cost associated with green bonds which comprises issuance cost, certification cost, and interest cost. Moreover, issuance of green bonds can lower the cost of debt of corporates (Zerbib,2019) apart from fulfilling their corporate social responsibility Flammer (2020). Kanamura, (2020), Flammer (2020), and Gianfrate & Peri (2019) have explained the performance of these bonds. Tang & Zhang (2020) have described how various stakeholders can be benefitted from these bonds. The need for switching to a clean source of energy is increasing (Mohsin et al., 2020; Saeed et al., 2020; Syed & Bouri, 2021). For instance, Saeed et al. (2020), explained how the green and non-green sources of energy are interconnected. Mohsin et al (2020), uncovered the hazardous effect of carbon dioxide on the environment and how the funding of green projects can help to reduce it.

Another significant strand of literature emphasizes the relationship of green bonds with commodities. For instance, Pham & Nguyen (2021) and Liu et al (2021), explain the relationship between green bonds and energy stocks. Pham & Nguyen (2021) found the spillover effect of green bonds on energy stock to be insignificant. Liu et al (2021), explained the spillover effect among green bonds and clean energy stocks from July 2011 to February 2020. The results prove that these markets react more aggressively towards bad news than against good news. The correlation between the green bonds and clean energy stocks was found positive. Clean energy stocks have more fluctuation as compared to green bonds market, where prices are governed by interest rates. Recently, Chai et al (2022) found a positive relationship between green bonds and the clean energy sector in the short run during the COVID-19 pandemic. The study also indicated that fostering good bonds during a financial downturn can help to minimize the hazardous impact of a crisis apart from fulfilling the funding requirement for to the clean energy sector. As per Pham (2021), energy commodities and MSCI influences the return on green equity whereas the prices of green bonds are impinged by movements in treasury and conventional bonds. Recently Rao et al (2022) have studied the relationship between green bonds and oil. The study pinnacled the safe haven properties of green bonds during the times of crisis.

The spillover shocks were more prominent during the short-term period. The volatility spillover from green bonds to green equity was significantly lower than their reverse impact. The connectedness between green equity and green bonds was found low, however during the financial crisis, the effect was significant. However, the spillover size of green equity and green bonds represents a very small fraction of the overall financial market.

Studies have also highlighted the hedging properties of green bonds (see for instance, Nguyen et al, 2020; Pham & Nguyen 2021; Naeem et al, 2021; Liu et al, 2021). More precisely, Pham & Nguyen (2021) suggested the use of green bonds with treasury and conventional bonds instead of energy stocks can diversify portfolio risk during the financial crisis. Nguyen et al (2020), urged the interdependency between green bonds and other financial assets to increase spontaneously aftermath of GFC 2008. Supporting this claim Naeem et al (2021), urged that the connectedness among green bonds and other financial assets has increased substantially during COVID-19 pandemic. Similarly, Naeem et al (2021) insinuated the fusion of green bonds with USD and gold for hedging portfolio risk during the non-crisis period.

The most recent studies have captured the interquartile connectedness in the green bond market and other asset classes. For instance, Phan (2021) applied cross quantilogram to support short-term coupling between green bonds and green equity during a boom. Arif et al. (2020), used cross quantilogram to compare the connectedness among green bonds and other assets at different quantiles. Wang et al (2022) applied causality in quantiles to investigate the relationship between green bonds, carbon, and clean energy stocks. While a growing body of literature documents the interconnection between the green bonds market and dirty energy, clean energy, and commodities, the directional and distributional predictability between green bonds and energy commodities is yet to be explored.

A notable study close to our paper is Naeem et al. (2022) who directly modeled the relationship between green bonds and the five energy markets using copulas. Our paper differs from these previous studies in several aspects. First, we have included a wide range of energy commodities comprising 3 green bond indices and 14 energy commodities indices. Second, we have explored the dependency between the two markets, particularly during COVID-19 pandemic. Third, we have applied cross quantilogram and causality-in-quantile methods on the given dataset. Since the market of green and sustainable finance is growing drastically and the world is transmitting towards environment-friendly practices. It becomes vital to understand the impact of green bonds on other financial markets. In this regard, the study contributes to the literature by documenting an in-depth connectedness between green bonds and crude oil, natural gas, petrol, kerosene, diesel, crude, heating oil, biofuels, and other energy commodities.

3. Empirical methodology

In this study, we employ the non-parametric causality-in-quantile modelling technique of Balcilar et al. (2016) to test for distributional predictability and the cross-quantilogram (CQ) method of Han et al. (2016) to test for directional predictability between green bond market and energy commodities during the COVID-19 outbreak.

3.1 Non-parametric causality-in-quantile method

To begin with, we adopt a relatively new causality-in-quantile estimation technique introduced by Balcilar et al. (2016) to explore the causality-in-mean and in-variance among the returns of green bond and energy commodities Following the spirit of Nishiyama et al. (2011) and Jeong et al. (2012), the mathematical model for the null hypothesis of Granger non-causality from x_t to y_t in the θ^{th} quantile with respect to the lag-vector of $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ is:

$$Q_\theta(y_t|y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) = Q_\theta(y_t|y_{t-1}, \dots, y_{t-p}) \qquad (1)$$

For a given explanatory vector, x_t Granger-causes y_t in the θ^{th} quantile with respect to $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ can be expressed as:

$$Q_\theta(y_t|y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) \neq Q_\theta(y_t|y_{t-1}, \dots, y_{t-p}) \qquad (2)$$

Here, $Q_\theta(y_t|\cdot)$ denotes the θ th quantile of y_t depending on t for all $\theta \in [0,1]$.

Let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, and $Z_t = (X_t, Y_t)$. The conditional distribution functions of y_t are then expressed by $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ given Z_{t-1} and Y_{t-1}, respectively. Here, $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is continuous in y_t for almost all Z_{t-1}. Let $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, and then $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ holds with a probability of one. Hence, the null hypothesis in Eqs. (1) and (2) can be specified as:

$$H_0\text{:} \quad P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1 \qquad (3)$$

$$H_1\text{:} \quad P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1 \qquad (4)$$

Following Jena et al. (2019) and Tiwari et al. (2022), we choose the bandwidth h=0.05 and adopt the Gaussian-type kernels for K (·) and L (·).

3.2 Cross-quantilogram (CQ) correlation framework

Another causality measure used in this study is the CQ method of Han et al. (2016), which examines the cross-quantile dependence among the series in a system. Its notable merit above other conventional measures of correlation is that it captures asymmetries in the cross-quantile dependence structure. Like the quantile cross-spectral approach, CQ requires that the series be stationary. Following the conventional practice in the literature, the estimates of the cross-quantile correlation are presented in heatmap forms for varying lags. The heatmaps offer a visual representation of the cross-quantile unconditional bivariate relationship between different distributions and allow for capturing the overall dependence structure visually and intuitively. Thus, the quantile distribution of any two series given as q = (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9) is shown on both the x-axis and the y-axis of a typical heatmap. The nine considered quantiles make the bivariate quantile combinations of the series be presented by 81 cells in each heatmap, with significant correlation specified by the presence of a star symbol in the cells.

For the specification, since the CQ approach follows the stationarity assumption for the underlying series, we let y_t and x_t be two time series that follow stationary stochastic processes. Given that $y_t = (y_{1t}, y_{2t})^T \mathcal{R}^2$ and $x_t = (x_{1t}, x_{2t})^T \mathcal{R}^{d_1} \times \mathcal{R}^{d_2}$,[1] a quantile function with the conditional distribution can be described as $F_{y_i|x_i}(\cdot\,|x_{it})$ and $q_{i,t}(\tau_i) = \{\upsilon\colon F_{y_i|x_i}(\upsilon|x_{it}) \geq \tau_i$ for any $\tau_i(0{,}1)$. The quantilogram method follows two steps. First, it calculates the quantile-hip process, which fundamentally captures serial dependency across the two events $y_{1t} \leq q_{1,t}(\tau_1)$ and

[1] In this case, $x_{it} = [x_{it}^1, \ldots, x_{it}^d]^T R^{d_i}$.

$y_{2,t-k} \leq q_{2,t-k}(\tau_2)$. Second, the cross-correlation between varying quantile-hits is further estimated.

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau 1}\left(y_{1,t}-q_{1,t}(\tau_1)\right)\psi_{\tau 2}\left(y_{2,t-k}-q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{E\left[\psi_{\tau 1}^2\left(y_{1,t}-q_{1,t}(\tau_1)\right)\right]}\sqrt{E\left[\psi_{\tau 2}^2\left(y_{2,t-k}-q_{2,t-k}(\tau_2)\right)\right]}} \qquad (5)$$

Here, $\psi_a = 1/[u < 0] - a$ indicates the quantile-hit process, which is examined under time $t - k$. Moreover, k is the number of lead-lag periods and refers to time t, while $\rho_\tau(k)$ measures the quantile-hit process correlation.

We note that CQ is a measure of the existence of directional predictability between two variables, and its derivation proceeds from the conditional quantiles. Considering two events given as $y_{1t} \leq q_{1,t}(\tau_1)$ and $y_{2,t-k} \leq q_{2,t-k}(\tau_2)$, there is an absence of directional predictability or cross-dependence if $\rho_\tau(k) = 0$. On the other hand, there is directional predictability or quantile dependence if $\rho_\tau(k) = 1$. The null hypothesis that the conditional correlations are significantly zero (i.e., $H_0: \rho_\tau(1) = \cdots = \rho_\tau(p) = 0$) is then tested against an alternative hypothesis of a significant difference from zero (i.e., $H_1: \rho_\tau(k) \neq 0$ for some $k \in \{1 \ldots \ldots \ldots . p\}$). To see a statistical inference in order to validate the null hypothesis, we employ the Box-Ljung test (Han et al., 2016), which is specified as:

$$\hat{Q}_\tau(p) = T(T+2)\sum_{k=1}^{p}\frac{\hat{\rho}^2(k)}{T-k} \qquad (6)$$

4. Data specification and summary statistics

The study uses daily closing price of S&P green bond index as an emblematic of global green bond market. The index was instigated in 2014 which comprises of green bonds issued by the municipal corporate, corporate bodies, industries and government. These bonds carry no minimum credit requirement; however, they must be labeled ‘green’. We have chosen S&P green bond index since they are most popular index for green bonds and has a wide recognition. Further most of the studies on green bonds have used S&P green bond index as a representator of global green bond market (Pham, 2021; Rao et al, 2022; Naeem et al,2022).

We have included a broad range of energy commodities in order to capture the in-depth view of the market with all variables defined Table 1. The commonly used commodities include S&P GSCI Natural Gas Spot, &P GSCI Brent Crude Spot, S&P GSCI WTI Index and S&P GSCI Heating Oil Spot. All these commodities are widely used in energy market studies (He et al,2012; Meng et al,2020; Naeem et al, 2021). However, we tried to focus the attention towards unfamiliar energy commodity such as S&P GSCI Biofuel Spot, S&P GSCI Unleaded Gasoline Spot, S&P GSCI Gas Oil Spot, OPEC Oil Basket Price, Crude Oil Oman, Crude Oil Dubai Cash and US Gulf Coast Kerosene and Los Angeles, Low Sulfur CARB Diesel Spot in order to capture the complete picture of the market.

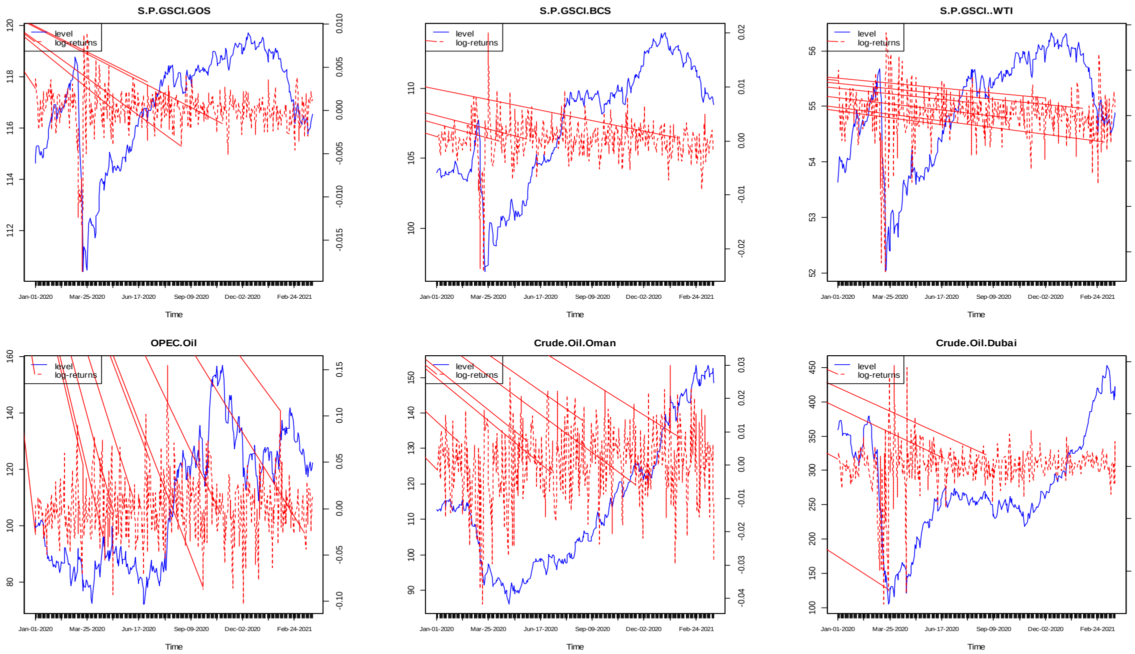
In past decide there was a substantial increase in environmental awareness, events like CoP have pinnacled the climate problems. Since then, there was a rise demand for clean energy commodities. Studies such as Chatziantoniou et al (2022) and Naeem et al (2022) have used S&P Global Clean Energy as a proxy for clean energy market. Likewise, we have also included S&P Global Clean Energy as a representer for clean energy market, in order to investigate it`s connectedness with green bonds. All these indices provide a comprehensive picture of all major energy commodities traded across the globe. We obtain data from the Datastream terminal for the period starting from January 1st, 2020 to March 26, 2021. We selected this sample period because it accounts for the various stages of the outbreak.

Table 1: Variables description

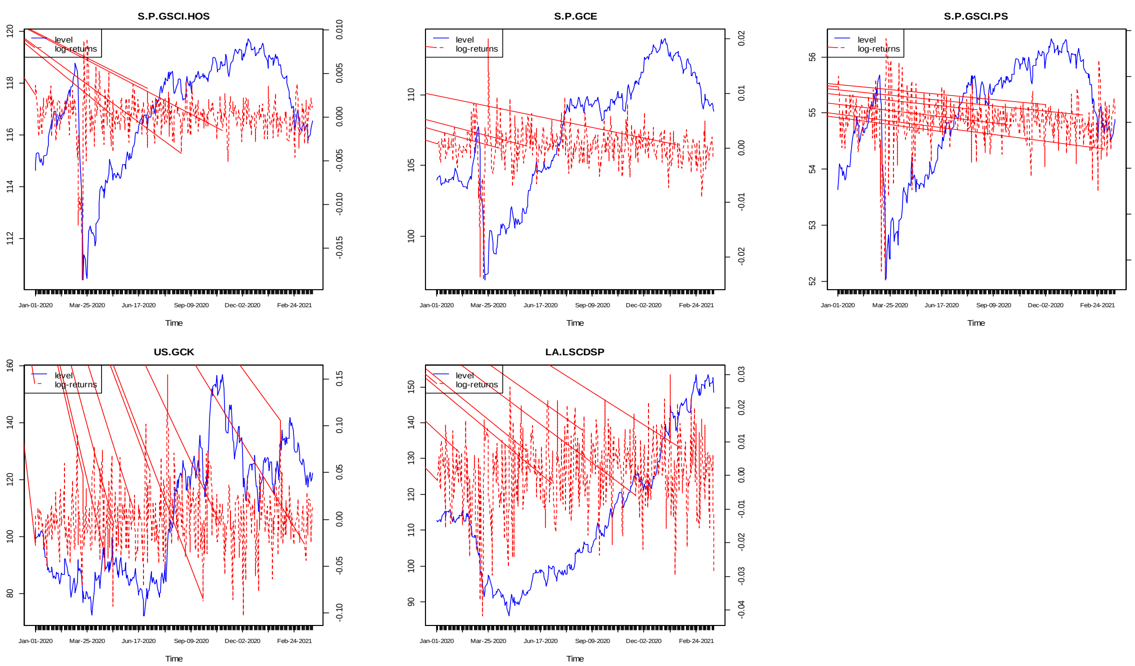
Label	Description of the indexes
S.P.GBSI	S&P GREEN Bond- PRICE INDEX
S.P.GSCI.NGS	S&P GSCI Natural Gas Spot - PRICE INDEX
S.P.GSCI.BS	S&P GSCI Biofuel Spot - PRICE INDEX
S.P.GSCI.UGS	S&P GSCI Unleaded Gasoline Spot - PRICE INDEX
S.P.GSCI.GOS	S&P GSCI Gas Oil Spot - PRICE INDEX
S.P.GSCI.BCS	S&P GSCI Brent Crude Spot - PRICE INDEX
S.P.GSCI.WTI	S&P GSCI WTI Index
OPEC. Oil	OPEC Oil Basket Price U$/Bbl
Crude. Oil. Oman	Crude Oil Oman M+1 U$/Bbl
Crude. Oil. Dubai	Crude Oil Dubai Cash U$/BBL
S.P.GSCI.HOS	S&P GSCI Heating Oil Spot - PRICE INDEX
S.P.GCE	S&P GLOBAL CLEAN ENERGY $ - PRICE INDEX
S.P.GSCI.PS	S&P GSCI Petroleum Spot - PRICE INDEX
US.GCK	US Gulf Coast Kerosene-Type Jet Fuel Spot Price
LA.LSCDSP	Los Angeles, Low Sulfur CARB Diesel Spot Price

The daily price levels and returns of seventeen markets including the financial and energy markets are shown in Figure 1. Prices in all markets plunged at the beginning of 2020 as a result of the financial stress due to the outbreak of the coronavirus pandemic. Among the various financial performance indexes, the price fall in S&P GSCI Natural Gas Spot, OPEC Oil Basket Price, and Crude Oil Oman continued till mid-2020. During late 2020, the market experiences an upward trend. The log return shows a tandem movement during pre-COVID 19 periods. During COVID-19, high volatility was noted for green bonds and all energy commodities.

Figure 1: Time series plot of daily price series and returns of green bonds and energy commodities.



Source: Authors own creation



Source: Authors own creation

The summary statistics for the daily returns for all financial indices, including statistics related to Jarque-Bera (JB) and unit root tests, are given in Table 2. All mean returns are positive, other than S&P

GSCI Gas Oil Spot, S&P GSCI WTI Index, US Gulf Coast Kerosene-Type Jet Fuel Spot Price, and Los Angeles, Low Sulfur CARB Diesel Spot Price. S&P Global Clean Energy Price Index has the highest mean returns. According to the standard deviations, OPEC Oil Basket Price is Staggering, while the least risky is green bonds. The values for kurtosis are positive, while skewness has negative values except for S&P GSCI Natural Gas Spot. Returns are distributed normally as shown evident from Jarque-Bera (JB) test. Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test, Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, and the Zivot Andrews (ZA) test show the unit root properties of the underlying series of observations. These tests conform the series to be stationary. Finally, the Ljung-Box tests show evidence of volatility clustering. ARCH-LM statistics show the presence of (autoregressive conditional heteroscedasticity) ARCH effects in the series.

Table 2: Descriptive statistics

	Mean	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	PP	KPSS	ZA	L-B	L-B^2	ARCH-LM(10)	Obs.
S.P.GBSI	0.000	0.003	-1.820 *	15.431 *	2244.1 *	-6.7979	-235.774	0.088383	-5.680 *	114.0 *	339.1 *	109.2 *	321
S.P.GSCI.NGS	0.001	0.034	0.395 *	4.554 *	40.7 *	-7.68454	-308.249	0.104889	-6.161 *	10.90406	9.558152	5.70786	321
S.P.GSCI.BS	0.001	0.011	-0.471 *	3.553456	16.0 *	-7.15342	-299.238	0.651804	-6.003 *	13.79139	40.0 *	21.42226	321
S.P.GSCI.UGS	0.000	0.044	-1.676 *	16.305 *	2517.9 *	-4.50413	-363.025	0.281345	-5.18799	26.3 *	150.9 *	70.2 *	321
S.P.GSCI.GOS	-0.001	0.031	-0.690 *	7.516 *	298.2 *	-5.80325	-319.524	0.544807	-5.887 *	40.8 *	160.3 *	52.3 *	321
S.P.GSCI.BCS	0.000	0.038	-1.354 *	17.856 *	3049.8 *	-5.66827	-319.776	0.358473	-5.873 *	16.06029	53.7 *	27.1 *	321
S.P.GSCI..WTI	-0.001	0.039	-1.804 *	21.932 *	4968.2 *	-4.94773	-389.145	0.557538	-5.26581	78.7 *	266.1 *	88.6 *	321
OPEC.Oil	0.000	0.049	-1.519 *	17.806 *	3055.4 *	-5.6381	-359.605	0.361472	-6.575 *	22.47325	86.4 *	31.0 *	321
Crude.Oil.Oman	0.000	0.047	-1.521 *	21.762 *	4832.1 *	-5.97824	-333.44	0.36567	-6.124 *	23.01879	36.4 *	16.47831	321
Crude.Oil.Dubai	0.000	0.039	-1.477 *	19.195 *	3624.9 *	-5.76175	-308.593	0.350363	-5.469 *	21.81973	37.1 *	23.13271	321
S.P.GSCI.HOS	0.000	0.031	-0.877 *	9.318 *	575.1 *	-6.16638	-329.155	0.582493	-6.077 *	19.03221	97.0 *	35.0 *	321
S.P.GCE	0.002	0.026	-0.870 *	7.749 *	342.2 *	-5.72619	-348.866	0.168944	-5.0264	48.6 *	246.5 *	80.3 *	321
S.P.GSCI.PS	0.000	0.043	-1.680 *	20.261 *	4135.9 *	-5.76098	-311.136	0.312579	-6.241 *	35.1 *	90.2 *	36.3 *	321
US.GCK	-0.001	0.045	-1.196 *	10.866 *	904.2 *	-4.83537	-367.404	0.361505	-5.482 *	24.2 *	97.7 *	32.0 *	321
LA.LSCDSP	-0.001	0.037	-1.382 *	10.316 *	818.2 *	-4.76534	-319.713	0.317657	-5.657 *	40.6 *	62.5 *	30.1 *	321

Note: The table reports the summary statistics for daily returns of all variables. Std. Dev denotes standard deviation. JB denotes the Jarque-Bera test for normality. ADF denotes Augmented Dickey and Fuller (1979), PP denotes Philip Perron and KPSS denotes Kwiatkowski–Phillips–Schmidt–Shin test. **L-B** and **L-B^2** are the Ljung-Box test for serial correlation in all series. ARCH(2) is the Lagrange multiplier test for autoregressive conditional heteroscedasticity of order 2. * denotes significance at 1%.

Source: Authors own creation

5. Empirical discussion

5. 1 Distributional predictability results: Causality-in-quantiles test.

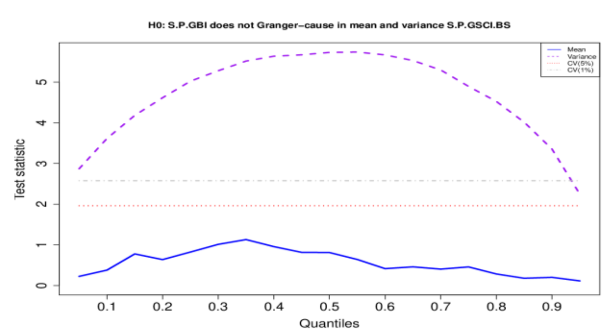
Causality Nexus: S&P Green Bond Index; S&P GSCI Natural Gas Spot; S&P GSCI Biofuel Spot; S&P GSCI B Unleaded Gasonline Spot; S&P GSCI Gas Oil Spot; S&P GSCI Brent Crude Spot; S&P GSCI WTI Spot; OPEC Oil Basket Spot; Crude Oil Oman Spot; Crude Oil Dubai Cash Spot; S&P GSCI Heating Oil Spot; S&P Global Clean Energy; S&P GSCI Petroleum Spot; US Gulf Coast Kerosene-Type Jet Fuel Spot Price and Los Angeles, Low Sulfur CARB Diesel Spot Price. Figure 2 shows the results of the causality-in-mean and causality-in-variance tests following the methodology by Balcilar et al. (2016). Markets are insulated as bearish, normal, and bullish based on the range of quantile distribution. In the given figure, the test-statistic on the non-parametric quantile causality test is denoted by the vertical axis, while various quantiles are represented by the horizontal axis. The level of significance at 5 percent and 10 percent is represented by grey and yellow lines respectively. The null hypothesis states Granger non-causality across energy commodities.

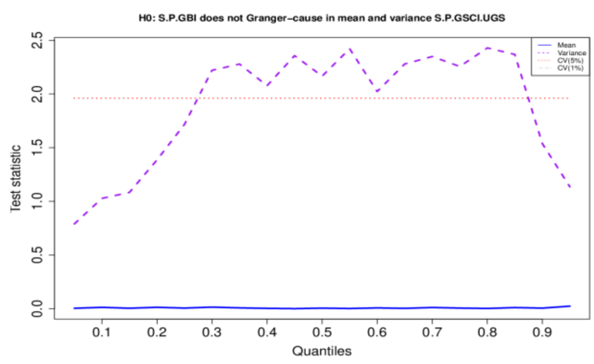
5.1.1 Green bonds and energy commodities

It is markable from Figure 2 for both the critical values at 5 percent levels and 10 percent levels, the nexus of the S&P Green Bond Index with S&P GSCI Biofuel Spot and S&P GSCI Natural Gas Spot, shows the rejection of the null hypothesis in - variance across all the quantiles but acceptance of the null hypothesis across all quantiles for quantile causality test in-mean. The same findings are demonstrated for S&P GSCI Gas Oil Spot, OPEC Oil Basket Spot , S&P GSCI WTI Spot, S&P GSCI Heating Oil Spot, S&P Global Clean Energy, Crude Oil Oman Spot and S&P Global Clean Energy, when fused with green bonds. As far as green bonds and S&P GSCI Gasonline is concerned we accept the null hypothesis for the granger causality test in-mean for both 10 percent and 5 percent levels of significance. In the case of the quantile causality test in variance between the green bonds and S&P GSCI Gasonline is concerned for both the critical values we find the rejection of the null hypothesis for the middle quantile distribution. Likewise, for the S&P GSCI Brent Crude Spot and Green Bonds market, we reject the null hypothesis across lower quantiles for quantile causality in mean but accept the null hypothesis for quantile casualty test in variance. A no causality-in-variance in the lower quantile implies that during bearish market conditions, the green bond market has no information predictability for the S&P GSCI Brent Crude Spot.

As far as the green bonds and the S&P GSCI Petroleum Spot is concerned we accept the null hypothesis for the granger causality test in-variance between 0.1 to 0.3 at a 10 percent and 5 percent confidence level. As far as the granger causality test in-mean is concerned, we reject the null hypothesis for the granger causality test in-variance between 0.1 to 0.3 at 10 percent and 5 percent confidence levels. Again, between green bonds and Los Angeles, Low Sulfur CARB Diesel Spot Price we accept the null hypothesis for the granger causality test in-variance across all quantiles but rejection null hypothesis for the granger causality test in-mean of at 10 percent and 5 percent confidence level.

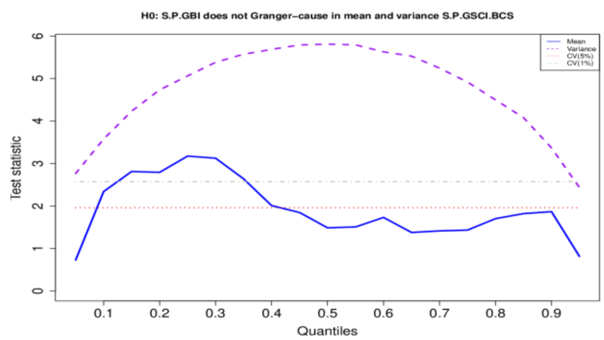
Figure 2: Quantile Causality in Mean and in Variance between Green Bonds and Energy Commodities

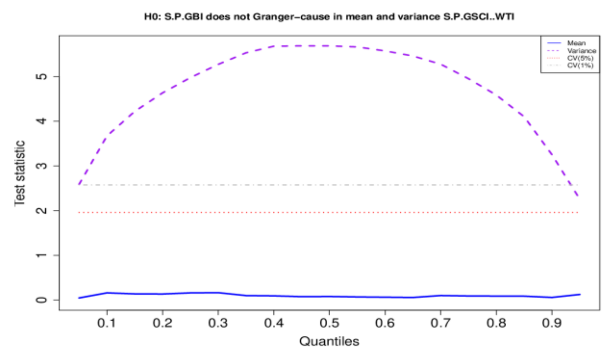
S&P Green Bond Index does not cause S&P GSCI Natural Gas Spot	**S&P GSCI Green Bond Index does not cause S&P GSCI Biofuel Spot.**
	
S&P Green Bond Index does not cause S&P GSCI Gasonline Spot	**S&P Green Bond Index does not cause S&P GSCI Gas Oil Spot**



S&P Green Bond Index does not cause S&P GSCI Brent Crude Spot

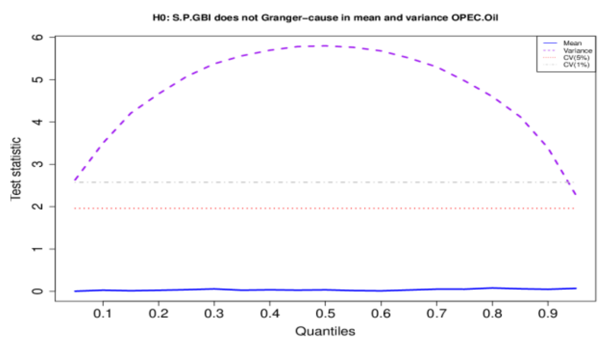
S&P GSCI Brent Crude Spot does not cause S&P GSCI WTI Spot





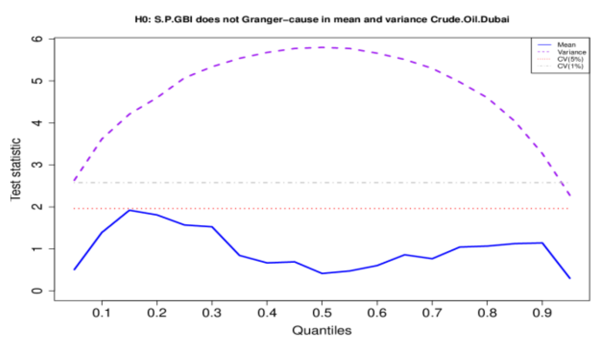
S&P Green Bond Index does not cause OPEC Oil Basket Spot

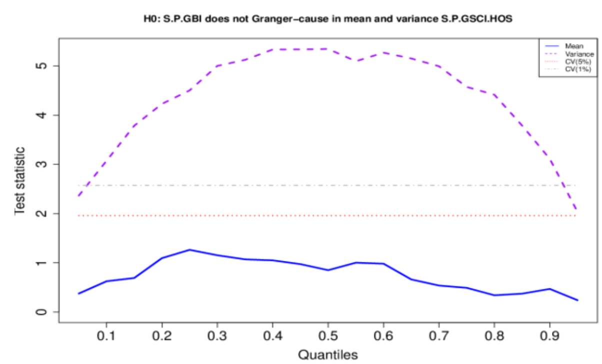
OPEC Oil Basket Spot does not cause Crude Oil Oman Spot



S&P Green Bond Index does not cause Crude Oil Dubai Cash Spot

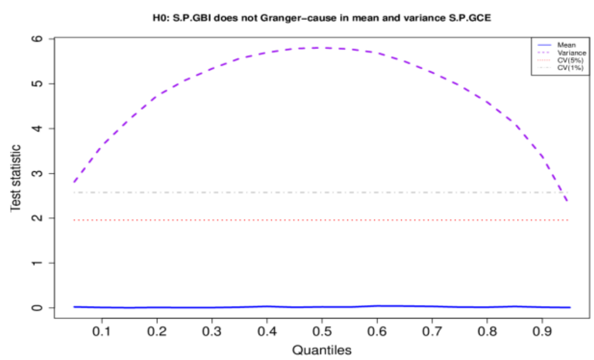
Crude Oil Dubai Cash Spot does not cause S&P GSCI Heating Oil Spot

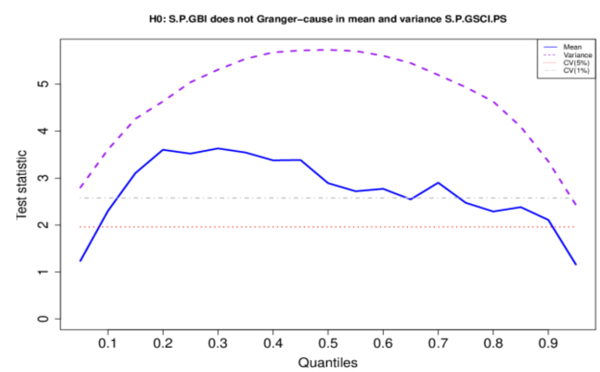




S&P Green Bond Index does not cause S&P Global Clean Energy

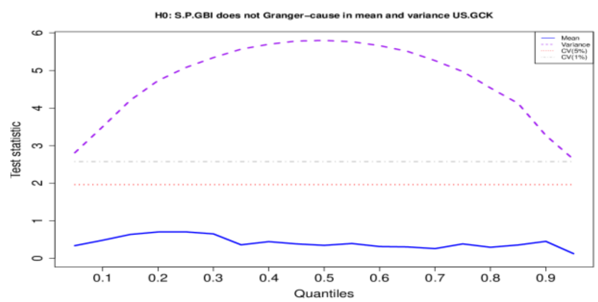
S&P Global Clean Energy does not cause S&P GSCI Petroleum Spot

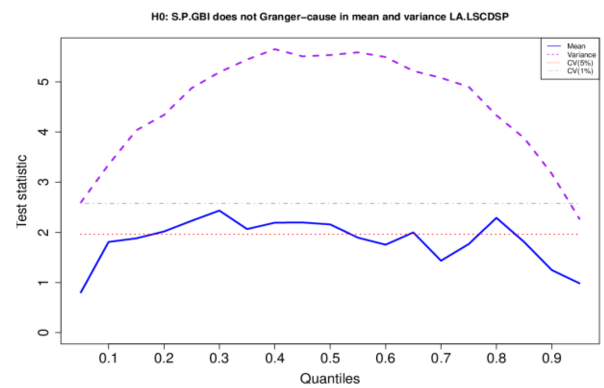




S&P Green Bond Index does not US Gulf Coast Kerosene-Type Jet Fuel Spot Price

US Gulf Coast Kerosene-Type Jet Fuel Spot Price does not cause Los Angeles, Low Sulfur CARB Diesel Spot Price





Note: Notes: The figure plots the estimates of the nonparametric causality test statistics (y-axis) corresponding to various quantiles (x-axis). The dark horizontal yellow and grey lines represent the 10% and 5% critical values, respectively. Source: Generated output on quantile causality test. Source: Authors own creation

To summarize the findings on the distributional predictability of energy commodities amid the green bonds market, we find strong evidence of asymmetry in causality across quantiles and strong variations across markets. Our results predominantly suggest to the investors that Los Angeles, Low Sulfur CARB Diesel Spot Price, can obtain predictability in information during normal market conditions when paired with green bonds. In bear regimes, there is no predictability in returns of the US Gulf Coast Kerosene and S&P Global Clean Energy with green bonds. For S&P GSCI Petroleum Spot, Crude Oil Dubai Cash Spot, Crude Oil Oman Spot, OPEC Oil Basket Spot, and S&P GSCI WTI Spot, the predictability is strong at the tail than the median. All these findings cast doubt on the 'safe-haven-properties' of these commodities during extreme market conditions. This indicates the existence of spillover effects of green bonds in the energy market namely S&P GSCI Gas Oil Spot , OPEC Oil Basket Spot, S&P GSCI WTI Spot, S&P GSCI Heating Oil Spot, S&P Global Clean Energy, Crude Oil Oman Spot, and S&P Global Clean Energy during normal market conditions. The reason behind negative correlation between green bonds and conventional energy could be that issuance of green bonds can ultimately promote the development for renewable source of energy, which eventually has negative impact on the demand for conventional energy (Nguyen et al., 2020).

Our findings exemplify the major conclusions in the extant literature on the valuable diversification properties of green bonds (Zerbib, 2016; Tang & Zhang, 2018; Reboredo et al., 2020; Naeem et al., 2021). The asset characteristics of green bonds and green bonds demonstrate that they cannot be used during stress periods. Our findings for the first time provide a broader horizon on the dependence on green bonds and energy commodities during COVID-19.

The results provide more concrete information on quantile causality from the slant of the policymakers, investors, and risk management. Thus, the results uphold the efficiency of the market under normal, bearish, and bullish periods. The overall directional predictability weakens during extreme market conditions. Our estimation using causality in quantiles adds to the existing literature on green bonds.

5.2 Directional predictability results

We have applied cross quantilogram within the framework of Han et al. (2016) in order to find the directional causality between green bonds and energy commodities. The novelty of this method is that it captures the correlations across various quantiles in distribution.[2]

5.1.1 Cross-Quantilogram between green bonds and energy commodities

[2] We only report results for the predictability between S&P Green Bond Index returns and energy commodities in the discussion. This is because, the results obtained in the case of the predictability between IShares Global Green Bond ETF and energy commodity is similar to what we recorded in the case of S&P Green Bond Index and energy commodities. Results are available upon request.

Table 3: Cross-Quantilogram Correlation between Green Bonds and Energy Commodities

Energy commodities	α = .05	α = .10	α = .50	α = .90	α = .95
S&P GSCI Natural Gas Spot	Negative	Negative	Negative	Negative	Negative
S&P GSCI Biofuel Spot	Positive	Positive	Negative	Negative	Negative
S&P GSCI B Unleaded Gasonline Spot	Positive	Positive	Negative	Negative	Negative
S&P GSCI Gas Oil Spot	Positive	Positive	Negative	Negative	Negative
S&P GSCI Brent Crude Spot	Positive	Positive	Negative	Negative	Negative
S&P GSCI WTI Spot	Positive	Positive	Negative	Negative	Negative
OPEC Oil Basket Spot	Positive	Positive	Negative	Negative	Negative
Crude Oil Oman Spot	Positive	Positive	Negative	Negative	Negative
Crude Oil Dubai Cash Spot	Positive	Positive	Negative	Negative	Negative
S&P GSCI Heating Oil Spot	Positive	Positive	Negative	Negative	Negative
S&P Global Clean Energy	Positive	Positive	Positive	Negative	Negative
S&P GSCI Petroleum Spot	Positive	Positive	Negative	Negative	Negative
US Gulf Coast Kerosene-Type Jet Fuel Spot Price	Positive	Positive	Negative	Negative	Negative
Los Angeles, Low Sulfur CARB Diesel Spot Price	Positive	Positive	Negative	Negative	Negative
Note: Detailed graphical plot on cross- quantilogram between green bonds and energy commodities is shown in annexure 1. *Source: Authors own creation*					

Table 3 shows a cross-quantilogram exploring the predictability from green bonds to GSCI B Unleaded Gasoline Spot, S&P GSCI Biofuel Spot, S&P GSCI Gas Oil Spot, S&P GSCI Brent Crude Spot , S&P

GSCI WTI Spot, OPEC Oil Basket Spot, Crude Oil Oman Spot , Crude Oil Dubai Cash Spot, S&P GSCI Heating Oil Spot, US Gulf Coast Kerosene-Type Jet Fuel Spot Price and Los Angeles, Low Sulfur CARB Diesel Spot Price. Across α =0.05 and α= 0.10, we obtain positive directional predictability and further negative directional predictability from α =0.50 to α =0.95. The findings indicate that a negative price change in green bonds causes a negative change in the aforesaid mention commodities under extreme market conditions. However, in case of bullish market conditions, a negative price change in green bonds causes an inverse change in GSCI B Unleaded Gasoline Spot, S&P GSCI Biofuel Spot, S&P GSCI Gas Oil Spot, S&P GSCI Brent Crude Spot, S&P GSCI WTI Spot, OPEC Oil Basket Spot, Crude Oil Oman Spot, Crude Oil Dubai Cash Spot, S&P GSCI Heating Oil Spot, US Gulf Coast Kerosene-Type Jet Fuel Spot Price and Los Angeles, Low Sulfur CARB Diesel Spot Price. Since issuance green bonds are positive impact on the environment, while use of conventional energy has a negative impact on the environment, so the green bonds and energy commodities have a negative relation with each other (Kanamura, 2020). This finding conforms to the affirmation of diversification and safe heaven properties of green bonds when fused with GSCI B Unleaded Gasoline Spot , S&P GSCI Biofuel Spot, S&P GSCI Gas Oil Spot, S&P GSCI Brent Crude Spot, S&P GSCI WTI Spot, OPEC Oil Basket Spot , Crude Oil Oman Spot , Crude Oil Dubai Cash Spot, S&P GSCI Heating Oil Spot, US Gulf Coast Kerosene-Type Jet Fuel Spot Price and Los Angeles, Low Sulfur CARB Diesel Spot Price under normal market conditions

In the case of green bonds and S&P Global Clean Energy, the results are positive from α =0.05 to α= 0.50 and further negative directional predictability across α =0.90 and α= 0.95. This indicates that under extreme market conditions prices of green bonds and S&P Global Clean Energy move in the same direction, while they move in the opposite directions in case of bullish market conditions.

The cross-quantilogram predictability between green bonds and S&P GSCI Natural Gas Spot is negative across all the quantiles from α =0.05 and α= 0.95, Which indicates that in the short run the prices of green bonds and S&P GSCI Natural gas move in opposite directions under both normal and extreme market conditions. Further, green bonds can act as a hedge under both market conditions when paired with natural gas.

Price formation for energy commodities depends upon macroeconomic factors to a large extent (Sifat et al., 2021). Emerging commodities can play a major role as alternative commodities, particularly under bearish market conditions. However, there is a need to dissect the properties of these commodities before accessing their predictability tendencies with green bonds.

There is a shift in investment patterns due to increasing instability in the global financial market. Which has resulted in the emergence of new financial asset markets like green bonds (Liu et al., 2021). This study is a spearhead that explores the shifting phenomena of interdependencies across the green bonds market vis-a-vis the energy commodities. Our study confers to the extant seam of literature on the interdependencies between green assets with other financial markets. This novel methodology on directional predictability captures the varying predictability tendencies across different market conditions.

6. Conclusion

This paper aims to examine the relationship between green investments and energy commodities during the outbreak of COVID-19. Specifically, we use the nonparametric causality in quantile and cross-quantilogram correlation approaches as the estimation techniques using daily spot prices from January 1, 2020, to March 26, 2021. We use S&P Green Bond Index as representatives of the global green bond market. For the energy commodity variables, we use spot prices of Natural Gas, Biofuel, Gasoline, Gas Oil, Brent Crude Oil, WTI Crude Oil, OPEC Oil, Crude Oil Oman, Crude Oil Dubai Cash, Heating Oil, Clean Energy, US Gulf Coast Kerosene and Diesel.

From the cross-quantilogram correlation results, there exists an overall negative directional predictability between green bonds and natural gas. We find that the directional predictability between green bonds and S&P GSCI Biofuel Spot , S&P GSCI Gas Oil Spot, S&P GSCI Brent Crude Spot, S&P GSCI WTI Spot, OPEC Oil Basket Spot, Crude Oil Oman Spot, Crude Oil Dubai Cash Spot, S&P GSCI Heating Oil Spot, US Gulf Coast Kerosene-Type Jet Fuel Spot Price and Los Angeles, Low Sulfur CARB Diesel Spot Price is negative during normal market conditions and positive during extreme market conditions. The reason behind it could be that during extreme market conditions the government has to focus to crab inflation and fulfill the energy demand in the market which renewable energy can`t substitute in the short time period. However, during normal market conditions, the government has ample time and resouces to promote and develop a clean energy market. Results from the non-parametric causality in the quantile approach show strong evidence of asymmetry in causality across quantiles and strong variations across markets. Results predominantly suggest to the investors that Los Angeles, Low Sulfur CARB Diesel Spot Price, can obtain predictability in information during normal market conditions when paired with green bonds. In bear regimes there is no predictability in returns of the US Gulf Coast Kerosene and S&P Global Clean Energy with green bonds, thereby highlighting the hedging properties of green bonds during a period of the financial crisis, which is supporting the claim of Arif et al (2021). The reason behind it could be that both green bonds and energy commodities such oil have opposite price movement as more investors prefer to shift towards fixed income assets like bonds (Rao et al., 2022). For S&P GSCI Petroleum Spot, Crude Oil Dubai Cash Spot, Crude Oil Oman Spot, OPEC Oil Basket Spot, and S&P GSCI WTI Spot, the predictability is strong at the tails than the median thereby reflecting the weak hedging properties of green bonds against these commodities.

Our findings have several implications. The findings have important implications. From a practical perspective, the quantile time-varying dependence and predictability results documented in this paper can help market participants with different investment targets and horizons adopt better hedging strategies and portfolio diversification to aid optimal policy measures during volatile market conditions. Investors given the immense benefits of green bonds are encouraged to enter the green bonds market. It allows corporate institutions to fulfill their social commitment through the issuance of green bonds. In addition, the results could be lucrative for the future volatility of green assets. Alternatively, the outcome of the study can be useful for financial institutions to predict the future market trend between green assets and energy commodities. Our results can aid traders of energy commodities to enhance their portfolio performance. To sum up, our research can be of great significance while framing strategies for asset allocation, portfolio performance, and risk hedging. From an academic standpoint, an analysis based on mean or middle dependence estimation will not capture the conditional distribution at extreme quantiles compared to the cross-quantilogram correlations and non-parametric causality in the quantile approach. Thus, the prevailing market conditions can impact the level and intensity of connectedness. In addition, the assumption that market participants and economic agents are homogeneous is not empirically documented. Hence, it is essential that any analysis of the relationship between green bonds and energy commodity markets take into account the premise that economic agents are homogeneous. From the policy perspective, policymakers' understanding and knowledge of whether a strong dependence, and predictably exists in financial markets under extreme positive and negative shocks will help guide decisions about whether specific policies are needed to protect investors from extreme fluctuations in the financial market, particularly during the times of financial crisis. Finally, it will aid to frame a policy that can reduce the financial impact of the COVID-19 pandemic on the spillover of shocks between green bonds and energy commodities, thereby simultaneously encouraging the participation of clean assets among investors. Future research can make a comparison of the connectedness among green assets and energy commodities during the financial crisis with a non-crisis period. Researchers can use dynamics of cross quantilogram switch between different regimes.

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