Green Bond, Renewable Energy Stocks and Carbon Price: Dynamic Connectedness, Hedging and Investment Strategies during COVID-19 pandemic

Aviral Kumar Tiwari[¶, *], Emmanuel Joel Aikins Abakah[†], David Gabauer[‡], and Richard Adjei Dwumbour[§]

[¶] *Rajagiri Business School, Rajagiri Valley Campus, Kochi, India.*
[†] *University of Cape Coast School of Economics, Cape Coast, Ghana.*
[‡] *Software Competence Center Hagenberg, Hagenberg, Austria.*
[§] *University of Ghana Business School, Accra, Ghana.*
[*] *Corresponding author: aviral.eco@gmail.com*

Abstract

This study has been inspired by the emergence of socially responsible investment practices in mainstream investment activity wherein it examines the transmission of return patterns between green bonds, carbon prices, and renewable energy stocks using daily data spanning from 1st January 2013 to 22nd September 2020. In this study, our dataset comprises the price indices of S&P Green Bond, Solactive Global Solar, Solactive Global Wind, S&P Global Clean Energy and Carbon. We employ the TVP-VAR approach to investigate the return spillovers and connectedness, and various portfolio techniques including minimum variance portfolio, minimum correlation portfolio and the recently developed minimum connectedness portfolio to test portfolio performance. Additionally, a LASSO dynamic connectedness model is used for robustness purposes. The empirical results from the TVP-VAR indicate that the dynamic total connectedness across the assets is heterogenous over time and economic event dependent. Moreover, our findings suggest clean energy dominates all other markets and is seen to be the main net transmitter of shocks in the entire network with Green Bonds and Solactive Global Wind emerging to be the major recipients of shocks in the system. Based on the hedging effectiveness, we show that bivariate and multivariate portfolios significantly reduce the risk of investing in a single asset except for Green Bonds. Finally, the minimum connectedness portfolio reaches the highest Sharpe ratio implying that information concerning the return transmission process is helpful for portfolio creation. The same pattern has been observed during the COVID-19 pandemic period.

Keywords: COVID-19, TVP-VAR, dynamic connectedness, portfolio management, hedging effectiveness, green bonds, renewable energy stocks, carbon price.
JEL codes: C32; C51; G15.

1 Introduction

Climate change has received a lot of attention from policy makers owing to its widespread effects on firms, households, and economies. The physical risk of climate change to economic agents emanating from natural disasters leads to the destruction of capital stock, loss of human lives and the disruption of economic activities (IMF, 2020). Indeed, Guo et al. (2021) project that by 2050, climate change will take away about 10% of global economic value if the rising temperature levels follow the current trajectory. For investors, particularly institutional investors with huge funds under their management, climate change poses high portfolio risks even though it also presents investment opportunities as well (Mercer, 2015). There are therefore renewed global commitments to cut global carbon emissions and reduce rising temperature levels in order to tackle climate change (IPCC, 2014). These commitments have focused on mitigation and adaptation strategies aimed at tackling climate change. Some of these strategies include renewable energy, issuance of green bonds, and carbon pricing.

The use of fossil fuels as a major source of energy over the decades has been the largest contributor to Green House Gas (GHG) emissions causing global warming and consequently increasing climate change. Renewable energy (RE) which includes wind, solar, water, biomass and wave among others, presents an alternative to fossil fuels to significantly reduce carbon emissions towards a sustainable economy as indicated in the 2015 Paris Climate Agreement and the UN Sustainable Development Goals. This has driven a lot of investor attention on renewable energy market. BP (2021) for instance show that investment in solar and wind capacity more than doubled between 2015 and 2020 equating to an annual growth of 18%. They project wind capacity to continue to increase at an annual rate of about 14% and solar capacity to also increase at an annual growth rate of about 18%. If these growth rates can be achieved, there is the need for more green finance in this market.

Hence, green finance in the form of green bonds is needed to finance new green projects and re-finance existing ones to help in the transition to low-carbon economy and progress towards a net-zero emission. Here, when the proceeds from a bond issuance is used to finance or re-finance green projects, this type of bond is classified as a green bond (ICMA, 2021). Since its first issuance in 2007 by the European Investment Bank, green bonds have gained attention as an alternative fixed-income asset especially for investors who want to be 'responsible investors' – that is investors who are environmentally conscious. This makes green bond a double-edged sword, that is, on one side, green bonds help to tackle climate change by financing green projects and on the other hand, green bonds present an opportunity for investors to diversify their portfolio and manage their risks. In fact, total green bond issuance reached a record US$258.9 billion in 2019 showing a 51% growth on 2018 (CBI, 2020). The largest share (38%) of the proceeds was used in the energy sector. This shows that most of the proceeds from green bonds are invested in renewable energy and to also improve energy efficiency. The question one may ask is: can green bonds be a hedge for renewable energy stocks?

To answer this question, the study examines how green bonds can be used as a hedge for renewable energy stocks. As found by Nguyen et al. (2021), green bonds have low and negative correlation with stocks and commodities no matter the period. Hence, the diversification property of green bonds may be useful as a hedge in a portfolio for renewable energy stocks. Quite compelling from their study is that the positive correlation among stocks and commodities were even heightened due to the global financial crisis (GFC) of 2007/2009. In a similar global crisis but this time a health pandemic (COVID-19), it would be interesting to know the connectedness between renewable energy stocks and to know the role of green bonds in this relationship during the vestiges of the COVID-19 pandemic. This is because the energy sector has been seriously hit by the COVID-19 pandemic. As indicated by Hosseini (2020) in a perspective paper, the rapid growth seen in the global renewable energy sector is confronted with threats from the COVID-19 pandemic; hence, the pandemic threatens to slow and possibly reverse the progress made in the sector. What seems rather to be in dearth are empirical studies that focus on the effect of COVID-19 on renewable energy stocks; Indeed, there are emerging studies that identify this theming gap and study this relationship. Liu et al. (2021) found that the uncertainties caused by COVID-19 on the returns and volatilities of renewable energy stocks is more significant than spillovers of uncertainties from the Global Financial Crisis (GFC).

Even scarcer in the literature are studies on the role of green bonds as a hedge for renewable energy stocks also taking into consideration the COVID-19 pandemic. The emerging studies on green bonds have been examined within the context of balanced fixed-income investment portfolio (Broadstock et al., 2020), connectedness with financial markets (Reboredo and Ugolini, 2020), as a hedge for carbon market risk (Jin et al., 2020), and finally as comovement with conventional bonds and commodities (Nguyen et al., 2021; Le et al., 2021) and other asset classes (Reboredo et al., 2020). Given its role in combating climate change, green bonds can act as a hedge for renewable energy stocks when the tides of global shocks like the COVID-19 pandemic blows against these stocks. This hedging property is particularly reinforcing given that investors in green bonds seem to be on a 'mission' – to say the least-to save the environment as a worthy course. This study therefore examines the dynamic connectedness between green bonds and renewable energy stocks and the hedging role of green bonds in this relationship.

On the flip side, the role of green bonds in promoting renewable energy stocks may be dampened if there is continuous investment in fossil fuels making renewable energy stocks unattractive and uncompetitive for investors; One may therefore ask: what role should governments/regulators play on the opposite end (fossil fuels) of the continuum of renewable energy to create the needed balance or swing the pendulum of investment to renewable energy stocks? Carbon pricing can be an effective way to swing this pendulum to renewable energy stocks. Carbon pricing is intended to reduce global emissions making the production of coal and other fuels costly while making renewable energy attractive. Hence, one would expect more investment in the renewable energy sector and its stocks as carbon prices increase. Indeed, Hanif et al. (2021) in a study that examined the dependence and connectedness between carbon pricing and renewable energy stock found high and strong spillover between carbon prices and renewable energy indices in the short run and long run irrespective of the time horizon. Their study showed positive dependence between carbon prices and renewable energy stocks. What our study seeks to do is to introduce carbon pricing to the dynamic framework between green bond and renewable energy stocks to give a bird's-eye view of these dynamic relationships.

Therefore, given the limited number of studies on green bonds and the emerging interest in using green bonds as a hedge against volatilities in stocks, commodities and other assets, there is the need to examine the hedging effect of green bonds for renewable energy stocks especially considering the COVID-19 pandemic and to able examine the role of carbon pricing in this relationship. This study fills this gap.

We make four main contributions to the literature. First, we provide new evidence by examining the connectedness between green bonds and renewable energy stocks using the TVP-VAR and LASSO-DY approaches. Second, we use portfolio approaches by constructing dynamic weighting schemes i– ncluding a novel minimum connectedness portfolio – to provide evidence on whether green bonds can act as a hedge for renewable energy stocks. Third, we examine the role of carbon price in this relationship. Fourth, we provide further robustness of these results during extreme market conditions like the COVID-19 pandemic.

The remaining sections of the paper are as follows: Section 2 gives a brief review of the emerging studies on green bonds, renewable energy and carbon pricing; Section 3 shows the methodology used to analyse the data; Section 4 describes the data used in the study; Section 5 presents and discusses the results while section 6 concludes the study and provides policy implications.

2 Literature review

The literature on renewable energy is gaining a lot of attention recently especially due to the renewed global calls to combat climate change. In the finance literature, studies on renewable energy stocks are gaining momentum especially on its relationship with other non-renewable energy stocks, energy commodities and crude oil prices.

On the relationship with non-renewable energy stocks and commodities, Asl et al. (2021) study the returns and volatilities spillovers between renewable energy index (S&P Global Clean Energy), the S&P Global Oil, along with natural gas and crude oil – both non-renewable energy commodities – and among other assets. The results showed that renewable energy index and the oil index have the highest optimal weights in their portfolio construction and that renewable energy stocks can be a good hedge for equity risks emanating from the oil and gas industries. On the crude oil prices, Ferrer et al. (2018) for instance examined the dynamic connectedness between US clean energy stocks and crude oil prices using the time-frequency connectedness methodology developed by Baruník and Křehlík (2018). The study documents strong connectedness in the short-run but not in the long-run. However, the study does not find crude oil prices to drive the performance of clean energy stocks. These results confirm the findings of Henriques and Sadorsky (2008) who also found a weak relationship between crude oil prices and renewable energy stocks in a vector autoregression (VAR) framework. Reboredo (2015) on the contrary found the existence of co-movement between crude oil prices and renewable energy stocks using a conditional Value-at-risk (CoVaR) approach. These results have implications for investors in the choice of their portfolios. Thus, depending on the risk profile of the investor in selection and allocation of portfolio assets, renewable energy remains an important asset that may have diversification advantages.

Meanwhile, given the ambiguous role of renewable energy stocks within a portfolio, empirical studies on green bonds are emerging as an alternative fixed-income asset that can act as a hedge for green bonds especially for climate-friendly investors. Sangiorgi and Schopohl (2021) through a survey of asset managers in European countries provide some insights into why these asset managers invest in green bonds. The study found majority of investors are actively invested in the green bond market and that most of these investors prefer green bonds that are issued by sovereign countries and corporations. The major determining factors of investors' choice of green bond are competitive pricing and the credentials of the green bond. These investors however prefer to invest in green bonds which have clear description of what green projects the proceeds would be used to finance. Monk and Perkins (2020) interviewed conference participants, reviewed relevant literature and trade publications, and interviewed experts to understand how the growth or diffusion of green bonds can be accelerated. The study found that most of the processes and dynamics associated with introducing innovation inspired frameworks in literature also apply to the growing innovation of green bonds. These include: the participation of various market actors in the process; processes that reinforce self-learning and legitimacy and a broad-based development approach in the conceptualization of the product as part of fixed-income assets.

The growing investor interest in green bonds and the scale of innovation or growth in green bonds market is quite intriguing even given the evidence of 'green premium'. Indeed, MacAskill et al. (2020) in a systematic literature review enquired whether green bonds have a 'green premium' or 'greenium' in their pricing. The study found consensus in the literature that show a consistent existence of green premium in about 56% of the studies in the primary market and around 70% of studies in the secondary market. This evidence is found especially for the type of green bonds that follow best practice and those that are issued by governments. This presupposes that the non-pecuniary motive of environmentally responsible investors is strong and growing. These findings suggest the role that green bonds can play in promoting renewable energy stocks and in combating global climate change.

While the environmental impact of green bonds remains unequivocal through the financing of green projects, the empirical question of the role of green bonds in the portfolio or asset class of investors remains an emerging empirical issue. Nguyen et al. (2021) recently studied the comovement among green bonds, conventional bonds, equities, commodities and clean energy from 2008 to 2019 using the rolling window wavelet correlation approach. The study found low and negative correlation of green bonds with stocks and commodities making magnifying the diversification benefit of green bonds. Our study differs from that of Nguyen et al. (2021) as we examine an array of renewable energy stocks and further examine the role of carbon pricing in this relationship. We further test the impact of the COVID-19 pandemic in this relationship.

To analyse the hedging effect of green bonds, Jin et al. (2020) examined the role of green bonds as an effective hedging instrument for carbon market risk. The study used three dynamic hedge ratio models including the DCC-APGARCH, DCC-T-GARCH, and DCC-GJR-GARCH models as well as the constant hedge ratio model (OLS model). The study found the green bond index to be the best hedge for carbon futures and that this relationship is time invariant. In an earlier study by Reboredo (2018), the author confirmed the large diversification benefits of green bonds for stocks and energy markets but negligible diversification benefit for corporate and treasury markets investors.

Reboredo et al. (2020) in a later study examined the connectedness between green bonds and different asset classes over different investment horizons in the EU and US asset markets. The study examined the dynamic correlations between green bonds and the asset classes using wavelet coherence while they examined connectedness using the forecast error variance decomposition of a multivariate VAR model. Unlike the earlier results of Reboredo (2018), the authors found strong connectedness between green bonds and corporate and treasury bonds in the EU and US markets. The authors found visible spillovers from corporate bonds and treasury bonds to green bonds but negligible transmission shocks from green bonds to the other bonds.

The literature on one hand shows the correlation and connectedness between crude oil, commodities, as well as, renewable and non-renewable energy stocks. On the other hand, a strand of literature also examines the correlation and connectedness between green bonds, other bonds, energy markets and equities. What appears to be missing which our study addresses are the correlation and connectedness between green bonds and renewable energy stocks. Even more compelling to examine is the role of carbon pricing and COVID-19 pandemic in this relationship.

3 Methodology

3.1 Time-varying parameter vector autoregression

To explore the time-varying linkages between clean energy, green bonds, wind, solar and carbon returns, we estimate a TVP-VAR model with heteroscedastic variance-covariances[1]. Based upon the Bayesian information criterion (BIC), a TVP-VAR(1) model is selected which can be mathematically formulated as,

$$\boldsymbol{y}_t = \boldsymbol{B}_t \boldsymbol{y}_{t-1} + \boldsymbol{\epsilon}_t \qquad \boldsymbol{\epsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_t) \tag{1}$$

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t \qquad \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \tag{2}$$

where $\boldsymbol{y}_t$, $\boldsymbol{y}_{t-1}$ and $\boldsymbol{\epsilon}_t$ are $K \times 1$ dimensional vector and $\boldsymbol{B}_t$ and $\boldsymbol{\Sigma}_t$ are $K \times K$ dimensional matrices. $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ are $K^2 \times 1$ dimensional vectors whereas $\boldsymbol{S}_t$ is a $K^2 \times K^2$ dimensional matrix. As the dynamic connectedness approach of Diebold and Yılmaz

[1]As the detailed algorithm is beyond the scope of this study interested readers are referred to Antonakakis et al. (2020a).

(2012, 2014) rests on the Generalised Forecast Error Variance Decomposition (GFEVD) of (Koop et al., 1996; Pesaran and Shin, 1998), it is required to transform the TVP-VAR to its TVP-VMA representation by the Wold representation theorem: $\boldsymbol{y}_t = \sum_{h=0}^{\infty} \boldsymbol{A}_{h,t} \boldsymbol{\epsilon}_{t-i}$ where $\boldsymbol{A}_0 = \boldsymbol{I}_K$.

The H-step ahead GFEVD models the impact a shock in series j has on series i. This can be formulated as follows,

$$\phi_{ij,t}^{gen}(H) = \frac{\sum_{h=0}^{H-1} (\boldsymbol{e}_i' \boldsymbol{A}_{ht} \boldsymbol{\Sigma}_t \boldsymbol{e}_j)^2}{(\boldsymbol{e}_j' \boldsymbol{\Sigma}_t \boldsymbol{e}_j) \sum_{h=0}^{H-1} (\boldsymbol{e}_i' \boldsymbol{A}_{ht} \boldsymbol{\Sigma}_t \boldsymbol{A}_{ht}' \boldsymbol{e}_i)} \tag{3}$$

$$gSOT_{ij,t} = \frac{\phi_{ij,t}^{gen}(H)}{\sum_{k=1}^{K} \phi_{ik,t}^{gen}(H)} \tag{4}$$

where $\boldsymbol{e}_i$ is a $K \times 1$ dimensional zero vector with unity on its ith position. As the $\phi_{ij,t}^{gen}(H)$ stands for the unscaled GFEVD ($\sum_{j=1}^{K} \zeta_{ij,t}^{gen}(H) \neq 1$), Diebold and Yılmaz (2009, 2012, 2014) suggested to normalize it by dividing $\phi_{ij,t}^{gen}(H)$ by the row sums to obtain the scaled GFEVD, $gSOT_{ij,t}$.

The scaled GFEVD is at the center of the connectedness approach facilitating the computation of the total directional connectedness to (from) all series from (to) series i. While the TO total directional connectedness constitutes the effect series i has on all others, the FROM total directional connectedness illustrates the impact all series have on series i. These connectedness measures can be calculated by,

$$S_{i \rightarrow \bullet,t}^{gen,to} = \sum_{j=1, i \neq j}^{K} gSOT_{ji,t} \tag{5}$$

$$S_{i \leftarrow \bullet,t}^{gen,from} = \sum_{j=1, i \neq j}^{K} gSOT_{ij,t}. \tag{6}$$

Computing the difference between the TO and the FROM total directional connectedness results in the net total directional connectedness of series i:

$$S_{i,t}^{gen,net} = S_{i \rightarrow \bullet,t}^{gen,to} - S_{i \leftarrow \bullet,t}^{gen,from}. \tag{7}$$

If $S_{i,t}^{gen,net} > 0$ ($S_{i,t}^{gen,net} < 0$), series i is influencing (influenced by) all others more than being influenced by (influencing) them and thus is considered to be a net transmitter (receiver) of shocks indicating that series i is driving (driven by) the network.

The connectedness approach also provides information on the bilateral level. The net pairwise directional connectedness shows the bilateral net transmission of shocks between series i and j,

$$S_{ij,t}^{gen,net} = gSOT_{ji,t} - gSOT_{ij,t}. \tag{8}$$

If $S_{ij,t}^{gen,net} > 0$ ($S_{ij,t}^{gen,net} < 0$), series i dominates (is dominated by) series j implying that series i influences (is influenced by) series j more than being influenced by (influencing) it.

The total connectedness index (TCI) is another relevant metric highlighting the degree of network interconnectedness and hence market risk. Considering that the TCI can be calculated as the average total directional connectedness to (from) others, it is equal to the average amount of spillovers one series transmits (receives) from all others. Chatziantoniou and Gabauer (2021) and Gabauer (2021) have shown that as the own variance shares are by construction always larger or equal to all cross variance shares the TCI is within $\left[0, \frac{K-1}{K}\right]$. To obtain a TCI which is within [0,1], we have to slightly adjust the TCI:

$$gSOI_t = \tfrac{1}{K-1} \sum_{i=1}^{K} S_{i \leftarrow \bullet,t}^{gen,from} = \tfrac{1}{K-1} \sum_{i=1}^{K} S_{i \rightarrow \bullet,t}^{gen,to}, \tag{9}$$

A high (low) value indicates high (low) market risk.

Finally, we calculate the pairwise connectedness index (PCI) which can be seen as the TCI on the bilateral level illustrating the degree of interconnectedness between series i and j. This can be formulated as:

$$PCI_{ij,t} = 2\left(\frac{gSOT_{ij,t} + gSOT_{ji,t}}{gSOT_{ii,t} + gSOT_{ij,t} + gSOT_{ji,t} + gSOT_{jj,t}}\right), \qquad 0 \leq PCI_{ij,t} \leq 1. \tag{10}$$

3.2 Portfolio back-testing models

To shed fresh insights on the hedging potential of green bond against renewable energy stocks and its financial significance, we use portfolio back testing approach to examine the investment performance of assets under examination. We use varied estimation approaches used in portfolio construction comprising of conventional approaches and some recent connectedness oriented portfolios. A number of assumptions underlines our portfolio analysis. These include: the index can be purchased by the investor directly, market participants are interested only in green bond and renewable energy stock investment and are open to invest in both green bonds and renewable energy stocks. Even though these assumptions are narrow, we argue that these assumptions are sufficient in illustrating our objective. Outlined below are a brief summary of the portfolio estimation approaches adopted.

3.2.1 Bilateral hedge ratios and portfolio weights

The dynamic hedge ratio of Kroner and Sultan (1993) can be formulated as follows,

$$\beta_{ij,t} = \mathbf{\Sigma}_{ij,t}/\mathbf{\Sigma}_{jj,t}, \tag{11}$$

where $\mathbf{\Sigma}_{ij,t}$ is the conditional covariance between series i and j at time t, and $\mathbf{\Sigma}_{jj,t}$ the conditional variance of series j at time t.

Kroner and Ng (1998) shows that the optimal bilateral portfolio weights between series i and j are calculated as,

$$w_{ij,t} = \frac{\mathbf{\Sigma}_{ii,t} - \mathbf{\Sigma}_{ij,t}}{\mathbf{\Sigma}_{ii,t} - 2\mathbf{\Sigma}_{ij,t} + \mathbf{\Sigma}_{jj,t}}, \tag{12}$$

with

$$w_{ij,t} = \begin{cases} 0, & \text{if } w_{ij,t} < 0 \\ w_{ij,t}, & \text{if } 0 \leq w_{ij,t} \leq 1 \\ 1, & \text{if } w_{ij,t} > 1 \end{cases} \tag{13}$$

where $w_{ij,t}$ is the weight of series i in a 1\$ portfolio between series i and j at time t. Thus, $1 - w_{ij,t}$ is the weight of series j at time t in the aforementioned portfolio.

3.2.2 Minimum Variance Portfolio (MVP)

A commonly used approach in portfolio analysis is the MVP method which attempts to create the portfolio with the least volatility founded on multiple assets as documented by

Markovitz (1959). The portfolio weights are estimated using the following formula:

$$\boldsymbol{w}_{\boldsymbol{\Sigma}_t} = \frac{\boldsymbol{\Sigma}_t^{-1}\boldsymbol{I}}{\boldsymbol{I}\boldsymbol{\Sigma}_t^{-1}\boldsymbol{I}} \tag{14}$$

where $\boldsymbol{w}_{\boldsymbol{\Sigma}_t}$ denotes the $K \times 1$ dimensioanl portfolio weight vector, $\boldsymbol{I}$ represents the K-dimensional vector of ones and $\boldsymbol{\Sigma}_t$ depicts the $K \times K$ dimensional conditional variance-covariance matrix in period t.

3.2.3 Minimum Correlation Portfolio (MCP)

In recent times, another procedure in the construction of portfolios emerged, namely the MCP that has been introduced by Christoffersen et al. (2014). This approach is similar to the MVP, however, in this case the portfolio weights are obtained byminimizing the conditional correlations and not the conditional covariances. This can be outlined as follows,

$$\boldsymbol{R}_t = diag(\boldsymbol{\Sigma}_t)^{-0.5}\boldsymbol{H}_t diag(\boldsymbol{\Sigma}_t)^{-0.5} \tag{15}$$

$$\boldsymbol{w}_{\boldsymbol{R}_t} = \frac{\boldsymbol{R}_t^{-1}\boldsymbol{I}}{\boldsymbol{I}\boldsymbol{R}_t^{-1}\boldsymbol{I}} \tag{16}$$

3.2.4 Minimum Connectedness Portfolio (MCoP)

Following the construction of the MVP and MCP portfolio techniques, we next generate MCoP by using the pairwise connectedness indices rather than the correlations or variances (Broadstock et al., 2020). The minimization of bilateral interconnectedness offer a portfolio procedure that is not affected heavily by network shocks. Thus, assets that are not influencing others and are not influenced by others are allocated with a higher weight in the constructed portfolio. This is expressed as shown below:

$$\boldsymbol{w}_{C_t} = \frac{\boldsymbol{PCI}_t^{-1}\boldsymbol{I}}{\boldsymbol{I}\boldsymbol{PCI}_t^{-1}\boldsymbol{I}} \tag{17}$$

$\boldsymbol{PCI}_t$ denotes the pairwise connectedness index matrix while the identity matrix is represented by $\boldsymbol{I}$.

3.2.5 Portfolio evaluation

To ascertain the performance of the portfolios, we rely on two metrics, the Sharpe ratio (Sharpe, 1994) and the hedging effectiveness (Ederington, 1979).

On the one hand, the Sharpe ratio (SR), also called the reward to volatility ratio, is computed as follows:

$$SR = \frac{\bar{r}_p}{\sqrt{var(r_p)}} \tag{18}$$

Where r_p represents the portfolio returns assuming that the risk-free rate is equal to zero. As higher SR values connotes higher returns relative to the level of risk in the portfolio, the SR allows us to compare various portfolios with each other as it informs us which portfolio has the highest return given the same volatility:.

The second metric is called Hedging Effectiveness (HE), which informs us about the risk percentage reduction the portfolio over investing in a single asset i. To know whether the reduction is significant we calculate the HE test statistics of Antonakakis et al. (2020b). The HE can be computed by,

$$HE_i = 1 - \frac{var(r_p)}{var(r_i)} \tag{19}$$

where $var(r_p)$ denotes the portfolio variance and $varr_i$ represents the variance of asset i's. The HE_i index shows the percentage reduction in the variance of the unhedged position of asset i. A high (low) HE index denotes a high (low) risk reduction.

4 Data

In this study, we examine the hedging and safe-haven properties of green bonds against renewable energy stocks by examining the return transmission and hedging effectiveness across numerous assets for the period of 1st January 2013 to 22nd September 2020. In more details, we use certificate prices of CO2 emissions (European Energy Exchange EU emissions trading system), S&P Green Bond Price Index (SPGRBND), and the following renewable energy stock indices: Solactive Global Solar (SOGLSOE), Solactive Global Wind (SOGLWIE), and S&P Global Clean Energy (SPGCLE$). All series are obtained from *Datastream*. As the raw series are non-stationary according to the ERS unit-root test, we base our analysis on daily percentage changes. Figure 1 and 2 report the time series plots of standardized raw series and returns, respectively. In Figure 1, we observe intense fluctuations in the price series of all assets under examination throughout the period. Interestingly, variations in prices and returns were even more pronounced during economic events such as the recent COVID-19 outbreak, the European governmental debt crisis, and the Brexit vote in 2016. Figure 2 reveals that multiple volatility clusters exist for all series except for green bond.

[INSERT FIGURES 1-2 AROUND HERE]

Table 1 presents the summary statistics of the daily returns. Focusing on the mean returns, we note that the daily mean is positive for all series. The highest mean is recorded for carbon price (0.12) followed by global wind (0.10), global solar (0.073), clean energy (0.049) and green bond (0.005). Thus, green bond recorded the lowest mean estimate whereas its standard deviation is also the lowest among all employed series. We find that all series are significantly left skewed and leptokurtic distributed which in turn leads to the fact that all series are statistically non-normally distributed on the 1% significance level. Furthermore, all series appear to be stationary, autocorrelated and exhibit ARCH/GARCH error on the 1% significance level. Interestingly, CO2 and green bonds seem to be not correlated with solar, wind and clean energy which is preferred for risk and portfolio management. This result is in-line with Reboredo (2018) and Jin et al. (2020). In addition, the highest correlations are observed between solar and clean energy followed by wind and clean energy. All those statistics support our choice to model the interrelationship among those variables using a TVP-VAR approach with time-varying variance-covariances.

[INSERT TABLE 1 AROUND HERE]

5 Empirical results

In this section, we discuss the averaged and dynamic results obtained from the employed TVP-VAR based connectedness approach which examines the return transmission mechanism between green bonds, carbon price and renewable energy stocks.

5.1 Averaged connectednes measures

Table 2 reports results for the TVP-VAR and the LASSO-VAR based connectedness approach. We note substantial variations in the magnitude of return shocks transmitted across variables. For the entire sample of variables under examination, we find green bonds transmit the lowest value of shocks to other markets (5.796%) followed by carbon price index returns (7.730%). The highest shock spillovers originate from clean energy to global solar (27.609%) followed by the propagation from global solar to clean energy (24.475%).

In the case of renewable energy stocks to green bond returns, we note that clean energy is the largest transmitter of shocks to green bond returns (1.855%) followed by global solar (1.515%) and wind (1.356%). Thus, renewable energy shocks transmit more shocks to green bonds compared to the number of shocks green bonds transmits to renewable energy stocks. Also, CO2 returns transmit more shocks to green bond (1.070%) than it receives from green bond (0.730%). In addition, we find that the average TCI is equal to 34.639% indicating that on average 34.639% of a shock in one variable spills to all others.

Focusing on the contribution to other assets, the gross directional volatility shocks transmitted to other assets from each of the individual assets returns under examination ranges from 2.246% for green bonds to 56.577% for clean energy. This estimate shows that about 56.719% of all others' forecast error variance can be explained by clean energy. It is also seen that 39.795% and 34.212% of the forecast error variance is caused by solar and wind, respectively, while Green bonds transmit only about 2.246% of the forecast error variance to other markets. Clearly, it can be seen that green bond have only a marginal effect on other markets. The range of the directional return shocks transferred from all other assets to one specific market ranges within 5.796% to 46.849%. We find that green bonds receives more shocks from other markets than it transmits to them. The same is seen for CO2, solar and wind. For example, solar receives 40.150% of its forecast error variance from other markets and transmits only 39.795% to others.

This leads us to the net directional connectedness measures which illustrate whether a series transmits more than it receives and hence be a net transmitter or vice versa a net receiver of shocks. Alternatively, we could indicate positive net spillover value as series that are spillover contributor while negative spillovers suggest that series are absorbing spillovers from others. We find that green bonds, global solar, global wind and carbon price are all net receivers of shocks with values equal to -2.523%, -0.361%,–3.534%, and -2.537%, respectively. This indicates that clean energy is dominating all others and hence the main net transmitter of shocks (9.728%) which again confirms the dominance of clean energy in the renewable energy market. For robustness purposes, we use the LASSO-VAR connectedness values which depicts a qualitatively similar picture concerning the networks transmission mechanism behavior.

Overall, we conjecture that the green bonds market is marginally integrated with renewable energy stocks in terms of the return transmission mechanism. We establish that renewable energy stocks have a significant effect on the green bond market compared to carbon price.

[INSERT TABLE 2 AROUND HERE]

5.2 Dynamic total connectedness

In this study, higher levels of the total connectedness index (TCI) connote strong connectedness among assets under examination. In other words, strong connectedness may suggest that the supposed risk relating to the green bond and renewable energy stocks and CO2 is increasingly equivalent indicating comparable market confidence. Figure 3 illustrate the total connectedness index which reveals the evolution of the total co-movement using TVP-VAR and LASSO VAR. Focusing first on the connectedness using TVP-VAR, we note that the magnitude of connectedness among assets under examination considerably varies over time and ranges from 25% (lowest) to about 62% (highest). This indicates that the magnitude of connectedness across the markets examined not only react to events associated with green bonds, renewable energy stocks and CO2 but may swiftly do so and by material amounts. A critical look at the TCI suggests that it assumed its lowest values in the beginning of 2018 and its largest values towards the end of 2020. Comparing the extent of connectedness, the existed during volatile markets states, we note high levels of connectedness during the COVID-19 period in 2020 compared to the level of connectedness that existed during the European governmental debt crisis and the Brexit vote in 2016. We make this claim because, the magnitude of connectedness reached its highest levels of about 62% during the COVID-19 in 2020 compared to TCI values of about 51% recorded in 2016. Comparing the TCI values obtained during bearish, normal, and bullish markets states show that, markets examined are not highly connected during normal markets states as seen for the period running from 2018-2019. In all, the level of connectedness during crisis-free period among these markets is minimal compared to crisis period. On the other hand, the TCI is seen to fluctuate considerably over time and not stable for the entire period. It levels increased marginally from about 25% in 2014 to about 40% in 2015 to 52% in 2016 before dropping sharply to around 25% in 2018 after which we witnessed a gradual increase in levels up to the beginning of 2020 of about 32%. The largest TCI is observed in January 2020 when the COVID-19 pandemic started reaching slightly more than 60%. For robustness purposes, we also report the TCI using LASSO results advanced by Gabauer et al. (2020) by the red line in Figure 3 which illustrates a similar pattern compared to the TVP-VAR approach.

[INSERT FIGURE 3 AROUND HERE]

5.3 Net total directional connectedness

In this section, we focus on the discussion on the net total directional connectedness. A key feature of the main estimation technique used in this paper is its ability to establish and distinguish whether a specific market in the entire system is a net transmitter or net receiver of shocks. Reported in Figure 4 is the net total directional connectedness index. The net spillovers are the difference between an asset's shocks contribution to others and the contribution of shocks an individual assets receives from other assets. Succinctly, a negative and positive net value indicates the individual asset is a net receiver of shocks and net transmitter of shocks respectively. For easy interpretation of Figure 4, an asset in the system is a net transmitter of shock to the system if the shaded area is in the positive region while an asset is regarded as a net receiver of shocks if the shaded area lies in the negative region. From Figure 4, we find that throughout the period, clean energy acts a transmitter of shock to other markets. In the case of green bonds, we find that green bond act as shock transmitters at some point and receivers of shocks at some stretches of time. We record same for solar, wind and carbon price. During the COVID-19 period, green bond seems to be a receiver of shocks together with wind and carbon price. However, clean energy and solar acted as transmitters of shocks during the COVID-19 period. Overall, the variation observed in each asset over time suggest a constantly evolving intensity attached to each market's role.

[INSERT FIGURE 4 AROUND HERE]

5.4 Net Pairwise total directional connectedness

Next we focus on the net pairwise directional connectedness to establish the exact role each market play with respect to other markets in the entire system. It is noteworthy to mention that the net total directional connectedness reported in Figure 4 is very useful in classifying which specific market in the system is a net transmitter or receiver of shocks. However, from the net pairwise directional connectedness reported in Figure 5, we are able to establish how one specific market impact the another market in the entire system. Focusing on the pairwise directional connectedness between CO2 and renewable energy stocks including solar, wind and clean energy suggest that CO2 is predominantly receives high levels of spillovers from renewable energy markets during volatile market states in 2016 and 2020. In the case of CO2-Solar and CO2-Clean energy we note there are stretches of time where CO2 transmits shocks to solar and clean energy in small quantities during normal markets states. In the case of CO2 and green bonds, we note that CO2 receives a marginal amount of shocks from green bond which occurred in 2019 and 2020. For all other periods, CO2 transmits large volume of shocks to green bond price returns. Concerning the pairwise spillovers between solar and other assets, we find that solar predominantly receives large quantity of shocks from clean energy for most periods and only transmits a minute quantity of shocks to clean energy around 2015. For solar-wind, solar-green, it is evident that wind and green bonds are net recipient of shocks from solar. Solar transmits more shocks to these assets than it receives from wind and green bond. Regarding the net pairwise directional connectedness between wind-clean energy and wind-green energy, we note some exciting outcomes. While wind is a net recipient of spillovers from clean energy for the entire period, green energy is also seen to be a recipient of shocks from wind. There only time green bond transmits shocks to wind occurred in 2019 which is even in smaller volume. Finally, we turn our attention to clean energy-green bond. As expected, clean energy transmits a great amount of shocks to green bond for the entire period except in 2018 where green bond is seen to transmit some amount of shocks to clean energy. Overall, the key information we obtain from Figure 5 is the transmission of net pairwise spillovers between CO2, green bonds and renewable energy markets and how they vary with time. The pattern of net pairwise spillovers reveal production and complementary relationships between green bonds and other assets.

[INSERT FIGURE 5 AROUND HERE]

5.5 Dynamic Pairwise Connectedness

This section provides a brief overview on the magnitude of connectedness across the paired markets discussed in Figure 5. Succinctly, Figure 6 reports the dynamic pairwise connectedness which addresses the question: how connected are paired markets? Thus, is green bond highly connected to renewable energy markets and CO2? This analysis is very significant and revealing since it expounds the level of connectedness among paired markets in the system and not connectedness among assets in the entire system. First, we focus on connectedness between CO2 and other assets in the system. We note that the magnitude of connectedness between CO2-Solar, CO2-Wind and CO2-Clean energy is minimal and follows the same pattern. We note that the level of connectedness increased tremendously during 2016 and 2020 periods. Thus, during bearish markets conditions, the connections between CO2 and renewable energy market increases. For the case of CO2-Green bond, the evidence of co-movement is extremely minimal. These two assets are predominantly not connected in most periods except in 2020 where we witnessed some form of connections. Second, we address the connectedness between solar and other assets in the network. Solar is seen to be highly connected with clean energy and wind. However, level of connectedness between Solar-Clean energy is higher compared to Solar-wind. Connectedness between Solar-Green bonds is marginal at all periods. Thirdly, wind-clean energy level of connectedness is extremely high at all periods. Finally, connectedness between wind-green bond and clean energy-green bond is seen to be less than 20% for the entire period. Thus, overall green bond is marginally connectedness to renewable energy market and CO2. This shows the diversification potential of green bond markets.

5.6 Portfolio and hedging strategies analysis

5.6.1 Bilateral hedge ratios and portfolio weights

Table 3 contains the summary statistics of hedge ratios and hedging effectiveness between the first assets to the second asset. The table reports that a $1 long position in the first asset can be hedged with the average value of hedge ratio percentage of short position in the second assets. For example, hedge ratio estimates for the case of solar/ wind which is 0.54$ reveal that a $1 long position in solar can be hedged for 0.54$ investment in wind. It is noteworthy to mention that the mean values of the solar/green bonds is negative. This arises when the asset pairs are correlated negatively. Thus, green bond can act as a good hedge against solar. Reported in Figure 7 is the graphical representation of hedge ratios for the bilateral portfolios. Focusing on the hedging effectiveness of paired assets, it can be seen that investment in Wind/Solar, Clean Energy/Solar, Solar/Wind, Clean Energy/Wind, CO2/Clean energy, Solar/Clean energy and wind/clean energy will reduce asset volatility evidenced by their positive HE values. Interestingly, these reductions in volatility are statistically significant at 1% level of significance indicating the reductions are financially meaningful. Figure 7 illustrates the bilateral hedge ratios summarized in Table 3. It can be observed that bilateral hedge ratios between assets under examination and green bond returns is insignificant as displayed in Figure 7.

[INSERT TABLE 3 AROUND HERE]

[INSERT FIGURE 7 AROUND HERE]

To deepen our understanding further on the investment implications of our study, we report in Table 4 the summary statistics of the bilateral portfolio weights and hedging effectiveness with the graphical outlook of Table 4 reported in Figure 8. We note that with the exception of the bilateral portfolio weights between green bonds and other assets under examination, investment in the portfolio weights of all paired assets reduces volatility per the statistical significance of the HE index for each paired asset. Figure 8 confirms the insignificance of the hedging effectiveness for green bond and other assets. Interestingly though is the fact that even no asset is helpful to hedge green bonds, green bonds are significantly reducing the investment risk of all other series.

[INSERT TABLE 4 AROUND HERE]

[INSERT FIGURE 8 AROUND HERE]

5.6.2 Multivariate portfolio analysis

Discussed in this section is the constructed multivariate investment portfolios based on the three approaches including MVP, MCP and MCoP approaches together with the hedging effectiveness discussed in section 3.2. We provide the dynamic portfolio weights reported in Figure 9 to shed further insights on the individual assets portfolio weights with the aim of providing more solid understanding on the composition of individual portfolio. From a closer look, it can be seen that the portfolio weights of MCP and MCoP differ only marginally while MVP nearly solely selects a single asset, namely green bonds.

Focusing on the specific asset weights, in the case of green bonds, we note intense fluctuation in the dynamic portfolio weights for all three approaches during COVID-19 period. We observe for MCoP, that there was a sharp change during the start of COVID-19 outbreak during the early days of 2020. However, during the peak of the pandemic, some assets reached portfolio weight record high. We also find intense nose diving in portfolio weights for green bond during the Brexit and the European governmental debt crisis. Similar results are obtained for the renewable energy stocks during the COVID-19 pandemic under MCoP. Regarding weights from MVP and MCP, we further note significant marginal differences comparing individual portfolio weights under MVP and MCP approaches. In all, we find significant qualitative differences in portfolio weights among the three approaches. Comparing the portfolio weights during bearish and bullish market conditions, we note portfolio weight during the COVID-19 period and other crisis period dropped and appreciated at some point in time compared to normal market states period.

[INSERT FIGURE 9 AROUND HERE]

After establishing that there exist marginal differences between the portfolio weights of MCP and MCoP, we next delve deeper focusing on the implications of our findings for portfolio and risk management purposes. Thus, we contrast and compare the conventional portfolio analysis approaches including MVP and MCP as well as recent approaches such as the MCoP by exploring the hedging effectiveness reported in Table 5 for MVP, MCP and MCoP portfolios, respectively. Among these three competing portfolio construction approaches, the MVP procedure aims to minimize portfolio volatility by definition. The MCP techniques on the other hand centers on reducing correlations across assets. Finally, the MCoP procedure minimizes pairwise connectedness or the bilateral return spillovers across assets.

To commence our analysis on the investment implications of our study, we first discuss briefly the average portfolio weights. It is evident from Table 5 following the average portfolio weights that green bond contributes significantly in a portfolio containing renewable energy stocks. This is because the portfolio weights for green bond ranges from about 30% of the allocated portfolio under MCP and MCoP approaches and approximately 97% for MVP for the entire period. Focusing on the renewable energy stocks, we observe some nuances, with global solar emerging as the asset with the largest portfolio weight among the renewable energy stocks in the case of MCP with average portfolio weight of 22% while global wind emerged as the renewable energy asset with largest portfolio weights under MCoP with portfolio weight of 21%. Interestingly, even though clean energy emerged as major transmitter of shock in the volatility analysis, it can be seen here that its contribution is trivial since clean energy recorded the least portfolio weight for both MCP and MCoP. This highlights the optimisation of MCP and MCoP as clean energy highly correlates with all others (Table 1) and is receiving and transmitting to others substantially (Table 2). The role of carbon price is also seen to be paramount under MCP (27%) and MCoP (27%). It is worth mentioning that the largest single weight in the constructed portfolio is also from the green bond. This findings is in consonance with the work of Broadstock et al. (2020) who examined minimum connectedness portfolios among green and black bonds around the world.

With reference to the hedging effectiveness ratios reported in Tables 5, we note from the MVP procedure that if we invested on average 0% in carbon price, 1% in global solar, global wind and clean energy and 97% in green bonds, then each asset volatility in the portfolio would be reduced by 1% for carbon price, 99% for global solar, global wind and clean energy and 2% for green bond. Interestingly, these reductions in volatility with the exception of green bond are statistically significant at 1% level of significance indicating the reductions are from a financial perspective meaningful.

Next, we focus on the portfolios from the MCP procedure. Findings suggest that investing 27% in carbon price, 22% in global solar, 18% in global wind, 3% in clean energy and 30% in green bond would reduce volatility of each asset by 89% for carbon price, 62% for solar, 37% for wind and 28% for clean energy while increasing asset volatility by -44.88% for green bond. Interestingly, all these reduction and increase in each asset's volatility are seen to be significant at 1% level.

Last but not least, we document concerning the MCoP approach that with the exception of green bond, investment of about 27% in carbon price, 20% in global solar, 21% in global wind, 4% in clean energy reduces increases asset volatility evidenced by the hedging effectiveness ratios. Thus, green bond is seen to increase asset volatility by 45% under MCoP. Comparing the weights under the three alternative portfolios show that the portfolio weights in the case MVP is less compared to MCP and MCoP. In all we provide evidence through the portfolio analysis the existence of some level of dynamic network which permits for diversification benefits.

[INSERT TABLE 5 AROUND HERE]

Finally, we report in Table 6, the Sharpe ratio for our three portfolio with results indicating that MCoP is the best performing portfolio with SR of 0.067 followed by MCP with SR of 0.065. The fact that the MVP has only a SR of 0.050 is of major interest for risk and portfolio managers, as initially it appears to be superior compared to MCP and MCoP as the volatility reduction has been much higher. However, the fact that the MVP heavily invested in green bonds lead to the case that the portfolio returns are also much smaller compared to all other portfolio techniques by nearly the factor ten.

[INSERT TABLES 6 AROUND HERE]

Discussed in this section is the constructed investment portfolios based on the three approaches including MVP, MCP and MCoP approaches. Figure 10 illustrates the alternative three constructed portfolios. Among the three portfolios, it can be seen that the performance of MCP and MCoP are identical sharing the same underpinning dynamic pattern recording a dip during the peak of COVID-19 in March-May 2020 before recording a sustained upward trajectory. Thus MCP and MCoP performs better than MVP approach.

[INSERT FIGURE 10 AROUND HERE]

5.6.3 Performance of multivariate portfolios during COVID-19 period

We note from Figure 11 the performance of all three multivariate portfolios for the COVID-19 period. As can be seen MCoP outperforms all other portfolios again. It is evident that during the peak of the virus, the performance of the portfolios declined marginally. However, the decline was only for a short period since the portfolios saw a sustained upward trajectory in their performance.

[INSERT FIGURE 11 AROUND HERE]

6 Conclusion and policy implications

This paper examines the transmission of risk patterns between green bond and renewable energy stocks taking into consideration the role of carbon price. This paper contributes to the emerging strand of literature on green investment following the emergence of socially responsible investment practices among market participants. Green investment have emerged as a popular scheme for both issuers and investors to satisfy the demand for socially accountable and impactful investment. In this budding space, renewable energy stocks has become a key international player, however, little attention has been offered towards their significant influence and role to the green bond market. We as a result questioned whether renewable energy stocks have a value enhancing role to play in a portfolio with green bonds and carbon price during crisis period such as COVID-19 period. To achieve this, we use S&P Green Bond Price Index as a measure of green bond and different renewable energy stocks indices: Solactive Global Solar, Solactive Global Wind, and

S&P Global Clean Energy. In addition, we include the certificate prices for CO2 emissions (European Energy Exchange EU emissions trading system) as a measure of carbon prices. The employed dataset runs from 1st January 2013 to 22nd September 2020. More specifically, we use TVP-VAR and LASSO VAR based dynamic connectedness approach to model the interconnectedness of our predetermined network and construct numerous bivariate and multivariate portfolios that informs us about the hedging effectiveness of all series and potential financial gains.

Regarding our question on the role of renewable energy stock to the green bond market and vice versa, we document several findings. On transmission from one market to another market, we find green bonds transmit the lowest value of volatility shocks to other markets followed by carbon price index returns. The highest spillovers are transmitted from clean energy to global solar (27.609%). In the case of return transmission from renewable energy stocks to green bond, we note that clean energy is the largest transmitter of shocks to green bond. In other words, renewable energy shocks transmits more shocks to green bonds compared to the amount of shocks green bonds transmits to renewable energy stocks. Focusing on the contribution to other assets, about 56.577% of the GFEVD of clean energy spilled to other assets under examination while 39.795% and 34.212% of the GFEVD of solar and wind respectively are transmitted to other markets. Green bond have marginal effects on renewable energy stocks since it only accounts for 2.246% of shocks to other markets. Concerning the range of the directional shocks transferred from all other assets to one specific market, we find the range to be wider from 7.730% to 46.849% for green bonds and clean energy, respectively. We find that green bonds receives more shocks from other markets compared to what it transmit to other markets. The same is seen for all the other assets. Overall, we note that green bonds, global solar, global wind and carbon price have negative net spillover values which indicates these assets are net receivers of shocks with global wind emerging to be the largest receiver of shocks in our entire sample followed by green bonds. The largest net transmitters in terms of magnitude in our sample is clean energy which again confirms the dominance of clean energy in the renewable energy markets.

On the performance of the investment portfolios constructed using MVP, MCP and

MCoP strategies, we again note a number of interesting findings. In general, we find suggestive evidence that the investment risk of all assets can be significantly reduced by creating portfolios. The only exception has been green bonds which in combination with others significantly reduced their investment risk, however, barely no combination has been found that significantly reduced the green bond investment risk. Notably, a lot of combinations have shown a higher reward to volatility ratio compared to green bonds. Regarding the dynamic portfolio weights, we establish that MCP and MCoP portfolio weights differ marginally from each other while MVP strongly focuses on green bonds nearly excluding all others from being part in the portfolio. Interestingly, we find that green bonds are difficult to hedge and also not helpful to hedge other assets when it comes to hedge ratios, however, creating bilateral portfolios has shown that green bonds help to significantly reduce the investment risk of other assets. However, barely no evidence has been found that carbon price or renewable energy stocks can reduce the risk of green bonds. Finally, in the multivariate portfolio setting, we have shown that all assets except for green bonds have been significantly reduced in their investment risk. Finally, our analysis shows that the MCoP portfolio reached the best performance.

The findings in this study proffer several implications. For market participants, our results can help in their portfolio composition since we show the diversification potential of green bonds to renewable energy stock returns. To the policymakers tasked to develop policies for the advancement of green bond markets, our findings on shock transmission from the green bond markets can help to enact policies that can ensure a smooth recovery process during different market conditions. With green bond receiving most shocks from renewable energy stocks, policy makers should consider green bonds and clean energy stocks to be interrelated assets in their policy framework. Future research may also consider other robust estimation techniques such as DCC.GARCH connectedness (Gabauer, 2020), the Markov-switching dependence model (Tiwari et al., 2021), joint connectedness (Lastrapes and Wiesen, 2021; Balcilar et al., 2021), as well as, fractional integration analysis techniques (Abakah et al., 2020; Gil-Alana et al., 2020).

References

Abakah, E. J. A., Gil-Alana, L. A., Madigu, G., and Romero-Rojo, F. (2020). Volatility persistence in cryptocurrency markets under structural breaks. *International Review of Economics & Finance*, 69:680–691.

Anscombe, F. J. and Glynn, W. J. (1983). Distribution of the kurtosis statistic b 2 for normal samples. *Biometrika*, 70(1):227–234.

Antonakakis, N., Chatziantoniou, I., and Gabauer, D. (2020a). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, 13(4):84.

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., and de Gracia, F. P. (2020b). Oil and asset classes implied volatilities: Investment strategies and hedging effectiveness. *Energy Economics*, 91:104762.

Asl, M. G., Canarella, G., and Miller, S. M. (2021). Dynamic asymmetric optimal portfolio allocation between energy stocks and energy commodities: Evidence from clean energy and oil and gas companies. *Resources Policy*, 71:101982.

Balcilar, M., Gabauer, D., and Umar, Z. (2021). Crude Oil futures contracts and commodity markets: New evidence from a TVP-VAR extended joint connectedness approach. *Resources Policy*, 73:102219.

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

BP (2021). Statistical Review of World Energy 2021, 70th edition. Technical report.

Broadstock, D. C., Chatziantoniou, I., and Gabauer, D. (2020). Minimum connectedness portfolios and the market for green bonds: Advocating socially responsible investment (SRI) activity. *Available at SSRN 3793771*.

CBI (2020). Green bonds global state of the market 2019. Accessed July 26, 2021. Technical report.

Chatziantoniou, I. and Gabauer, D. (2021). EMU risk-synchronisation and financial fragility through the prism of dynamic connectedness. *The Quarterly Review of Economics and Finance*, 79:1–14.

Christoffersen, P., Errunza, V., Jacobs, K., and Jin, X. (2014). Correlation dynamics and international diversification benefits. *International Journal of Forecasting*, 30(3):807–824.

D'Agostino, R. B. (1970). Transformation to normality of the null distribution of g1. *Biometrika*, pages 679–681.

Diebold, F. X. and Yılmaz, K. (2009). Measuring Financial Asset Return And Volatility Spillovers, With Application To Global Equity Markets. *Economic Journal*, 119(534):158–171.

Diebold, F. X. and Yılmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28:57–66.

Diebold, F. X. and Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134.

Ederington, L. H. (1979). The hedging performance of the new futures markets. *The Journal of Finance*, 34(1):157–170.

Ferrer, R., Shahzad, S. J. H., López, R., and Jareño, F. (2018). Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. *Energy Economics*, 76:1–20.

Fisher, T. J. and Gallagher, C. M. (2012). New weighted portmanteau statistics for time series goodness of fit testing. *Journal of the American Statistical Association*, 107(498):777–787.

Gabauer, D. (2020). Volatility impulse response analysis for DCC-GARCH models: The role of volatility transmission mechanisms. *Journal of Forecasting*, 39(5):788–796.

Gabauer, D. (2021). Dynamic measures of asymmetric & pairwise spillovers within an optimal currency area: Evidence from the ERM I System. *Journal of Multinational Financial Management*, page 100680.

Gabauer, D., Gupta, R., Marfatia, H., and Miller, S. M. (2020). Estimating us housing price network connectedness: Evidence from dynamic elastic net, lasso, and ridge vector autoregressive models.

Gil-Alana, L. A., Mudida, R., and Abakah, E. J. A. (2020). Are central bank policy rates in Africa cointegrated? Evidence from a fractional cointegration approach. *Applied Economics*, 52(57):6171–6182.

Guo, J., Kubli, D., and Saner, P. (2021). The economics of climate change: No action not an option. Technical report.

Hanif, W., Hernandez, J. A., Mensi, W., Kang, S. H., Uddin, G. S., and Yoon, S.-M. (2021). Nonlinear dependence and connectedness between clean/renewable energy sector equity and European emission allowance prices. *Energy Economics*, page 105409.

Henriques, I. and Sadorsky, P. (2008). Oil prices and the stock prices of alternative energy companies. *Energy Economics*, 30(3):998–1010.

Hosseini, S. E. (2020). An outlook on the global development of renewable and sustainable energy at the time of COVID-19. *Energy Research & Social Science*, 68:101633.

ICMA (2021). Green bond principles: Voluntary process guidelines for issuing green bonds. Technical report.

IMF (2020). Climate change: Physical risk and equity, global financial stability report: Markets in the time of COVID-19. Technical report.

IPCC (2014). Climate change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Technical report.

Jarque, C. M. and Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, 6(3):255–259.

Jin, J., Han, L., Wu, L., and Zeng, H. (2020). The hedging effect of green bonds on carbon market risk. *International Review of Financial Analysis*, 71:101509.

Koop, G., Pesaran, M. H., and Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1):119–147.

Kroner, K. F. and Ng, V. K. (1998). Modeling asymmetric movements of asset prices. *Review of Financial Studies*, 11(04):817–844.

Kroner, K. F. and Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis*, 28(04):535–551.

Lastrapes, W. D. and Wiesen, T. F. (2021). The joint spillover index. *Economic Modelling*, 94:681–691.

Le, T.-L., Abakah, E. J. A., and 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.

Liu, T., Nakajima, T., and Hamori, S. (2021). The impact of economic uncertainty caused by COVID-19 on renewable energy stocks. *Empirical Economics*, pages 1–21.

MacAskill, S., Roca, E., Liu, B., Stewart, R., and Sahin, O. (2020). Is there a green premium in the green bond market? Systematic literature review revealing premium determinants. *Journal of Cleaner Production*, page 124491.

Markovitz, H. M. (1959). *Portfolio selection: Efficient diversification of investments*. John Wiley.

Mercer, L. (2015). Investing in a time of climate change. *London, UK: Mercer International Finance Corporation and the UK Department for International Development.*

Monk, A. and Perkins, R. (2020). What explains the emergence and diffusion of green bonds? *Energy Policy*, 145:111641.

Nguyen, T. T. H., Naeem, M. A., Balli, F., Balli, H. O., and Vo, X. V. (2021). Time-frequency comovement among green bonds, stocks, commodities, clean energy, and conventional bonds. *Finance Research Letters*, 40:101739.

Pesaran, H. H. and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1):17–29.

Reboredo, J. C. (2015). Is there dependence and systemic risk between oil and renewable energy stock prices? *Energy Economics*, 48:32–45.

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

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

Reboredo, J. C., Ugolini, A., and Aiube, F. A. L. (2020). Network connectedness of green bonds and asset classes. *Energy Economics*, 86:104629.

Sangiorgi, I. and Schopohl, L. (2021). Why do institutional investors buy green bonds: Evidence from a survey of European asset managers. *International Review of Financial Analysis*, 75:101738.

Sharpe, W. F. (1994). The sharpe ratio. *Journal of Portfolio Management*, 21(1):49–58.

Stock, J., Elliott, G., and Rothenberg, T. (1996). Efficient tests for an autoregressive unit root. *Econometrica*, 64(4):813–836.

Tiwari, A. K., Abakah, E. J. A., Le, T.-L., and Leyva-de la Hiz, D. I. (2021). Markov-switching dependence between artificial intelligence and carbon price: The role of policy uncertainty in the era of the 4th industrial revolution and the effect of COVID-19 pandemic. *Technological Forecasting and Social Change*, 163:120434.

Table 1: Summary Statistics

	CO2	Solar	Wind	Clean Energy	Green
Mean	0.12	0.073	0.102	0.049	0.005
Variance	10.697	3.158	1.879	1.642	0.026
Skewness	-0.419***	-0.855***	-0.170***	-0.791***	-1.281***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Kurtosis	11.886***	15.452***	4.792***	13.961***	13.251***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	11948.980***	20343.073***	1942.665***	16614.814***	15331.672***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-4.028***	-6.271***	-2.460**	-3.569***	-9.820***
	(0.000)	(0.000)	(0.014)	(0.000)	(0.000)
$Q(20)$	36.727***	78.728***	25.878***	85.520***	83.680***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
$Q^2(20)$	180.342***	26.131***	861.534***	1626.783***	1171.520***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
			Unconditional correlations		
	CO2	Solar	Wind	Clean Energy	Green
CO2	1.000	0.043	0.055	0.070	-0.0004
Solar	0.043	1.000	0.301	0.507	-0.042
Wind	0.055	0.301	1.000	0.427	0.005
Clean Energy	0.070	0.507	0.427	1.000	-0.019
Green	-0.0004	-0.042	0.005	-0.019	1.000

Notes: ***,**,* denote significance at 1%, 5% and 10% significance level; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Stock et al. (1996) unit-root test with constant; $Q(10)$ and $Q^2(10)$: Fisher and Gallagher (2012) weighted portmanteau test.

Table 2: TVP-VAR: Averaged Dynamic Connectedness Table

	CO2	Solar	Wind	Clean Energy	Green	FROM others
CO2	92.270 (92.264)	2.230 (2.071)	2.204 (2.280)	2.523 (2.655)	0.772 (0.730)	7.730 (7.736)
Solar	1.625 (1.412)	59.850 (59.189)	10.398 (10.689)	27.609 (28.034)	0.518 (0.675)	40.150 (40.811)
Wind	1.412 (1.340)	11.574 (11.744)	61.971 (62.019)	24.589 (24.510)	0.453 (0.386)	38.029 (37.981)
Clean Energy	1.618 (1.498)	24.475 (25.250)	20.254 (20.371)	53.151 (52.236)	0.502 (0.645)	46.849 (47.764)
Green	1.070 (0.948)	1.515 (1.385)	1.356 (1.107)	1.855 (1.519)	94.204 (95.040)	5.796 (4.960)
TO	5.724 (5.199)	39.795 (40.450)	34.212 (34.447)	56.577 (56.719)	2.246 (2.436)	TCI
NET	-2.005 (-2.537)	-0.355 (-0.361)	-3.817 (-3.534)	9.728 (8.955)	-3.550 (-2.523)	34.639 (34.813)

Notes: Results are based on a TVP-VAR model with lag length of order 1 (BIC) and a 20-step-ahead forecast. Values in parentheses represents the measures based upon the LASSO results of Gabauer et al. (2020) while the others demonstrates measures of the Antonakakis et al. (2020a) approach.

Table 3: Bilateral Hedge Ratios

	Mean	Std.Dev.	5%	95%	HE	p-value
Solar/CO2	0.04	0.11	-0.07	0.30	0.04	0.34
Wind/CO2	0.05	0.07	-0.02	0.22	0.03	0.46
Clean Energy/CO2	0.06	0.10	0.00	0.32	0.04	0.30
Green/CO2	0.00	0.00	-0.01	0.01	0.02	0.72
CO2/Solar	0.06	0.28	-0.39	0.66	0.05	0.22
Wind/Solar	0.33	0.16	0.16	0.62	0.25	0.00
Clean Energy/Solar	0.46	0.21	0.20	1.00	0.53	0.00
Green/Solar	0.00	0.01	-0.02	0.01	0.02	0.67
CO2/Wind	0.24	0.21	-0.08	0.60	0.05	0.25
Solar/Wind	0.54	0.14	0.32	0.89	0.29	0.00
Clean Energy/Wind	0.55	0.20	0.32	1.13	0.48	0.00
Green/Wind	0.00	0.01	-0.02	0.02	0.02	0.62
CO2/Clean Energy	0.23	0.23	-0.07	0.70	0.12	0.01
Solar/Clean Energy	1.05	0.21	0.74	1.41	0.64	0.00
Wind/Clean Energy	0.74	0.15	0.51	0.96	0.53	0.00
Green/Clean Energy	0.00	0.01	-0.01	0.02	0.03	0.51
CO2/Green	0.01	1.87	-2.44	3.48	0.03	0.55
Solar/Green	-0.36	0.99	-2.26	1.23	0.02	0.63
Wind/Green	0.02	0.61	-1.19	0.88	0.02	0.57
Clean Energy/Green	0.05	0.57	-1.03	1.08	0.02	0.59

Notes: Results are based on Kroner and Sultan (1993).

Table 4: Bilateral Portfolio Weights

	Mean	Std.Dev.	5%	95%	HE	p-value
CO2/Solar	0.23	0.13	0.10	0.57	0.78	0.00
CO2/Wind	0.15	0.14	0.04	0.56	0.85	0.00
CO2/Clean Energy	0.11	0.11	0.03	0.38	0.86	0.00
CO2/Green	0.00	0.00	0.00	0.01	1.00	0.00
Solar/CO2	0.77	0.13	0.43	0.90	0.26	0.00
Solar/Wind	0.28	0.12	0.13	0.59	0.49	0.00
Solar/Clean Energy	0.11	0.26	0.00	1.00	0.53	0.00
Solar/Green	0.01	0.01	0.00	0.03	0.99	0.00
Wind/CO2	0.85	0.14	0.44	0.96	0.16	0.00
Wind/Solar	0.72	0.12	0.41	0.87	0.14	0.00
Wind/Clean Energy	0.31	0.26	0.04	1.00	0.34	0.00
Wind/Green	0.02	0.02	0.00	0.05	0.99	0.00
Clean Energy/CO2	0.89	0.11	0.62	0.97	0.10	0.02
Clean Energy/Solar	0.89	0.26	0.00	1.00	0.10	0.02
Clean Energy/Wind	0.69	0.26	0.00	0.96	0.24	0.00
Clean Energy/Green	0.02	0.01	0.00	0.04	0.99	0.00
Green/CO2	1.00	0.00	0.99	1.00	0.01	0.79
Green/Solar	0.99	0.01	0.97	1.00	0.05	0.27
Green/Wind	0.98	0.02	0.95	1.00	0.06	0.19
Green/Clean Energy	0.98	0.01	0.96	1.00	0.05	0.23

Notes: Results are based on Kroner and Ng (1998).

Table 5: Multivariate Portfolio Weights

	Minimum Variance Portfolio					
	Mean	Std.Dev.	5%	95%	HE	p-value
CO2	0.00	0.00	0.00	0.01	1.00	0.00
Solar	0.01	0.01	0.00	0.04	0.99	0.00
Wind	0.01	0.02	0.00	0.05	0.99	0.00
Clean Energy	0.01	0.01	0.00	0.03	0.98	0.00
Green	0.97	0.03	0.90	0.99	0.02	0.38
	Minimum Correlation Portfolio					
	Mean	Std.Dev.	5%	95%	HE	p-value
CO2	0.27	0.03	0.20	0.30	0.89	0.00
Solar	0.22	0.03	0.17	0.28	0.62	0.00
Wind	0.18	0.05	0.10	0.27	0.37	0.00
Clean Energy	0.03	0.04	0.00	0.11	0.28	0.00
Green	0.30	0.03	0.26	0.35	-44.88	0.00
	Minimum Connectedness Portfolio					
	Mean	Std.Dev.	5%	95%	HE	p-value
CO2	0.27	0.02	0.25	0.30	0.89	0.00
Solar	0.20	0.02	0.17	0.23	0.62	0.00
Wind	0.21	0.02	0.16	0.24	0.36	0.00
Clean Energy	0.04	0.04	0.00	0.11	0.27	0.01
Green	0.28	0.02	0.26	0.32	-45.39	0.00

Notes: Results of MVP, MCP and MCoP are based on Markovitz (1959), Christoffersen et al. (2014) and Broadstock et al. (2020), respectively.

Table 6: Sharpe Ratio

	MVP	MCP	MCoP
Mean	0.008	0.071	0.073
Std.Dev.	0.159	1.090	1.097
SR	0.050	0.065	0.067

Notes: Results are based on Sharpe (1994).

Figure 1: Standardized Raw Series

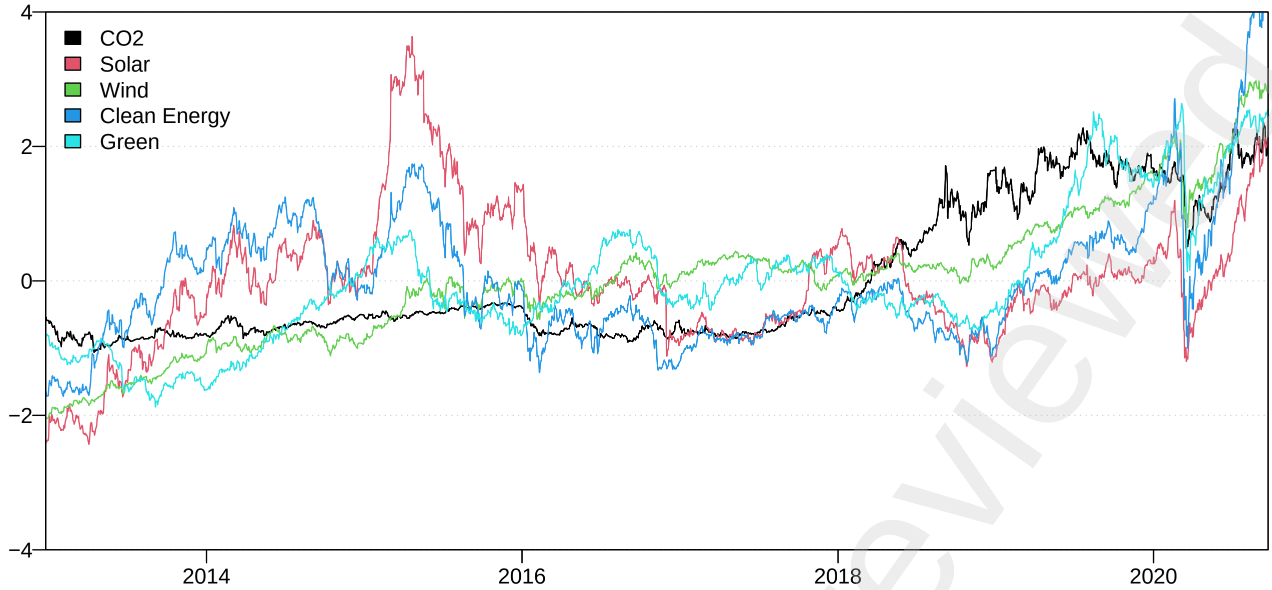


Figure 2: Returns

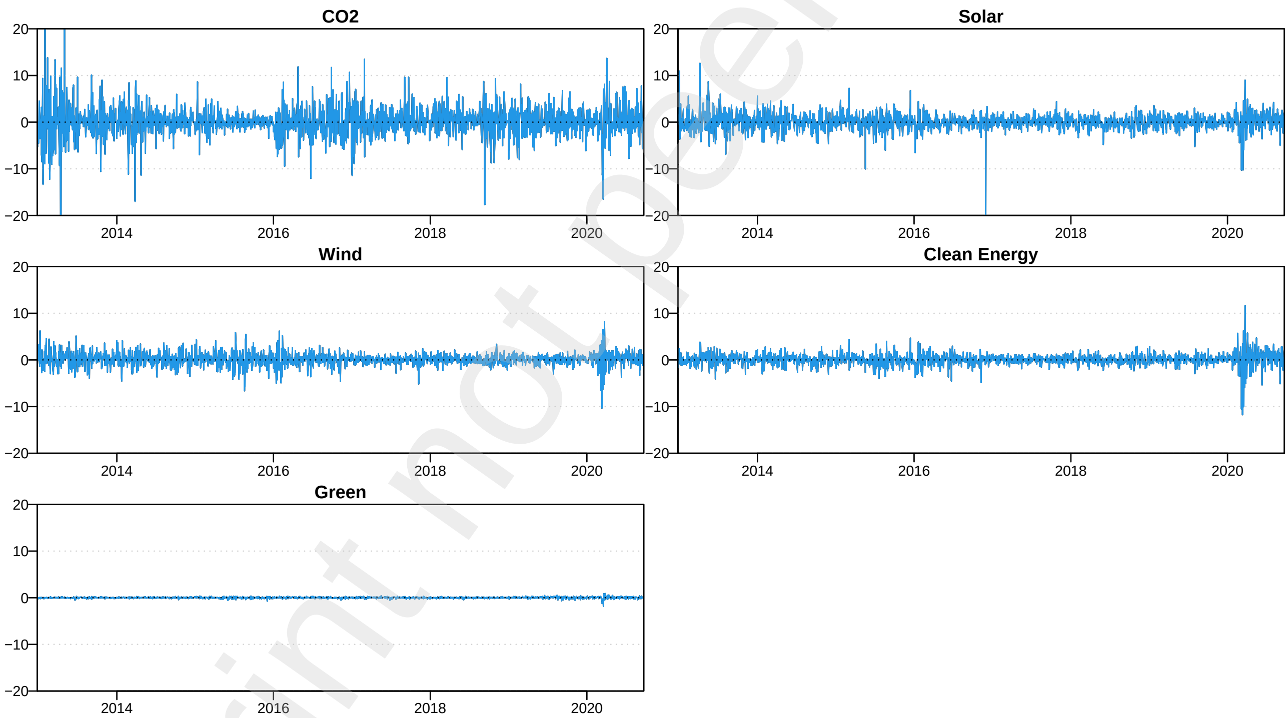
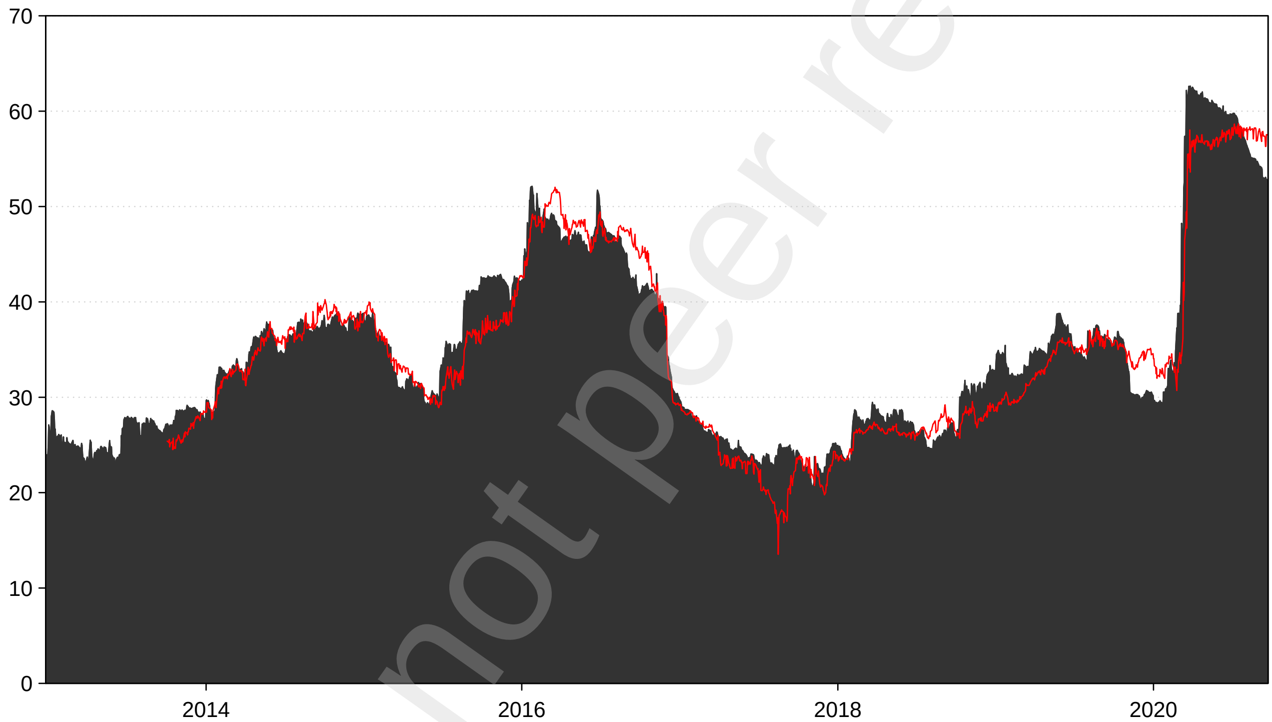
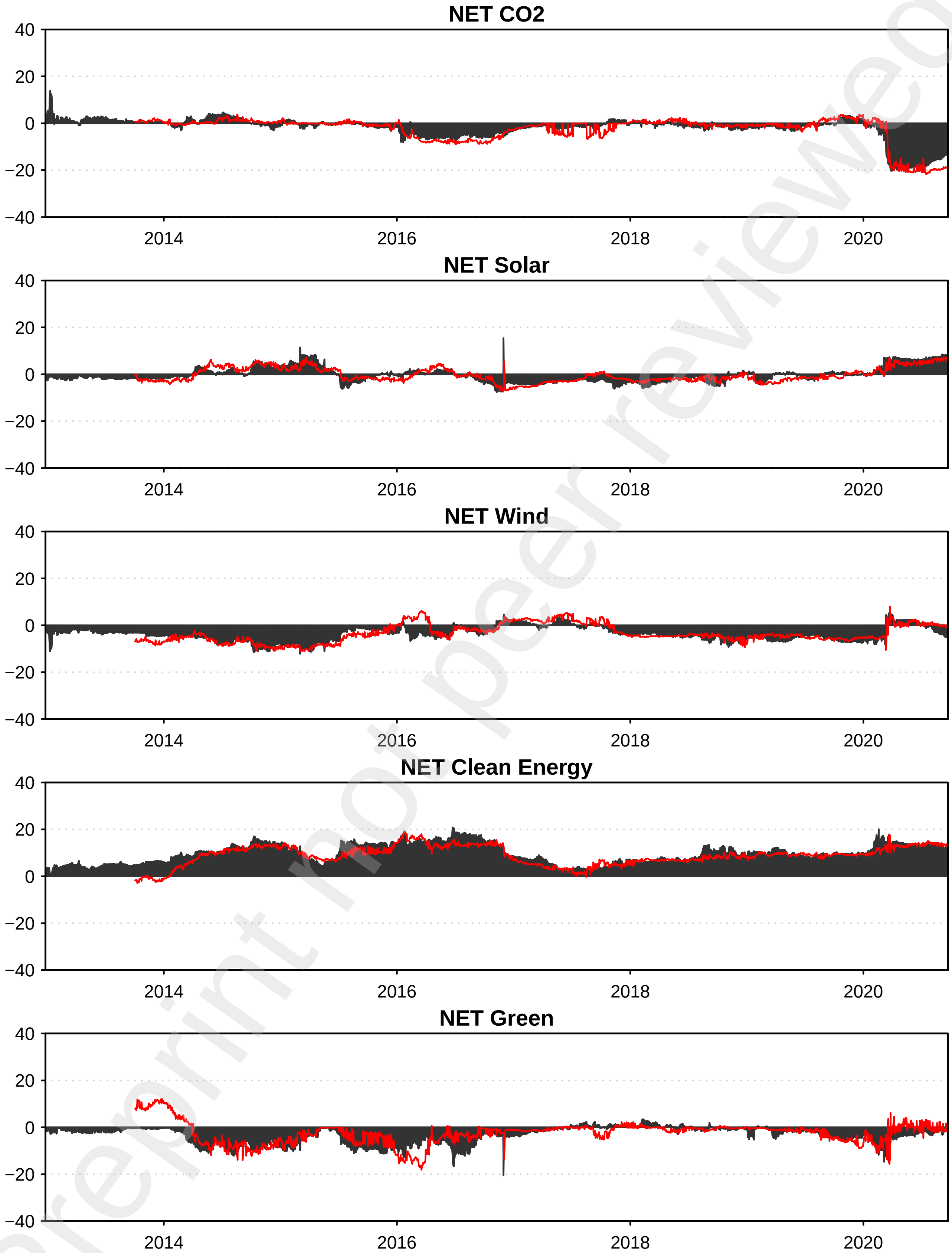


Figure 3: Dynamic Total Connectedness



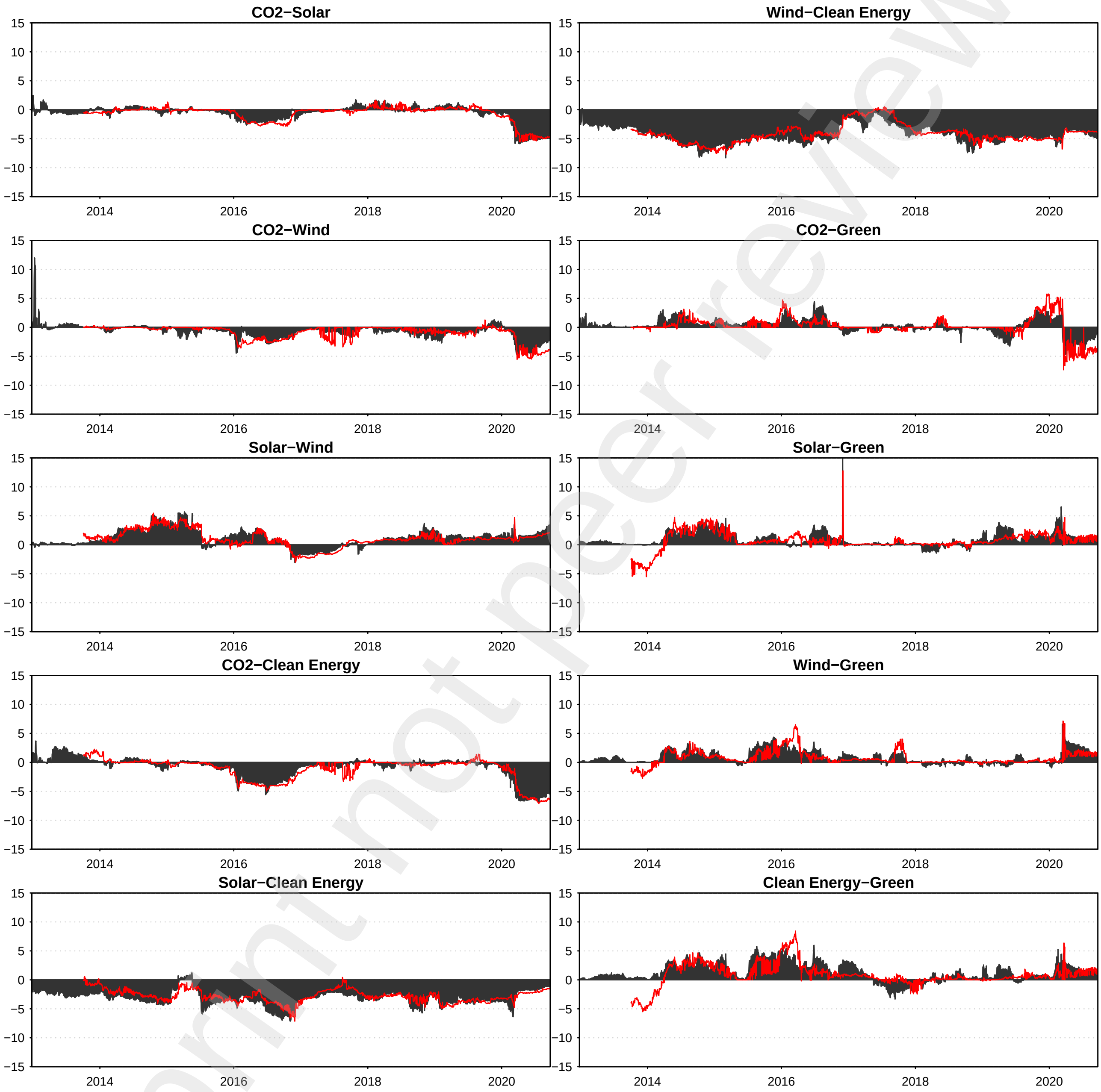
Notes: Results are based on a TVP-VAR model with lag length of order 1 (BIC) and a 20-step-ahead forecast. The black area represents the measures based upon the Antonakakis et al. (2020a) approach while the red line demonstrates the LASSO results of Gabauer et al. (2020) results.

Figure 4: Net Total Directional Connectedness



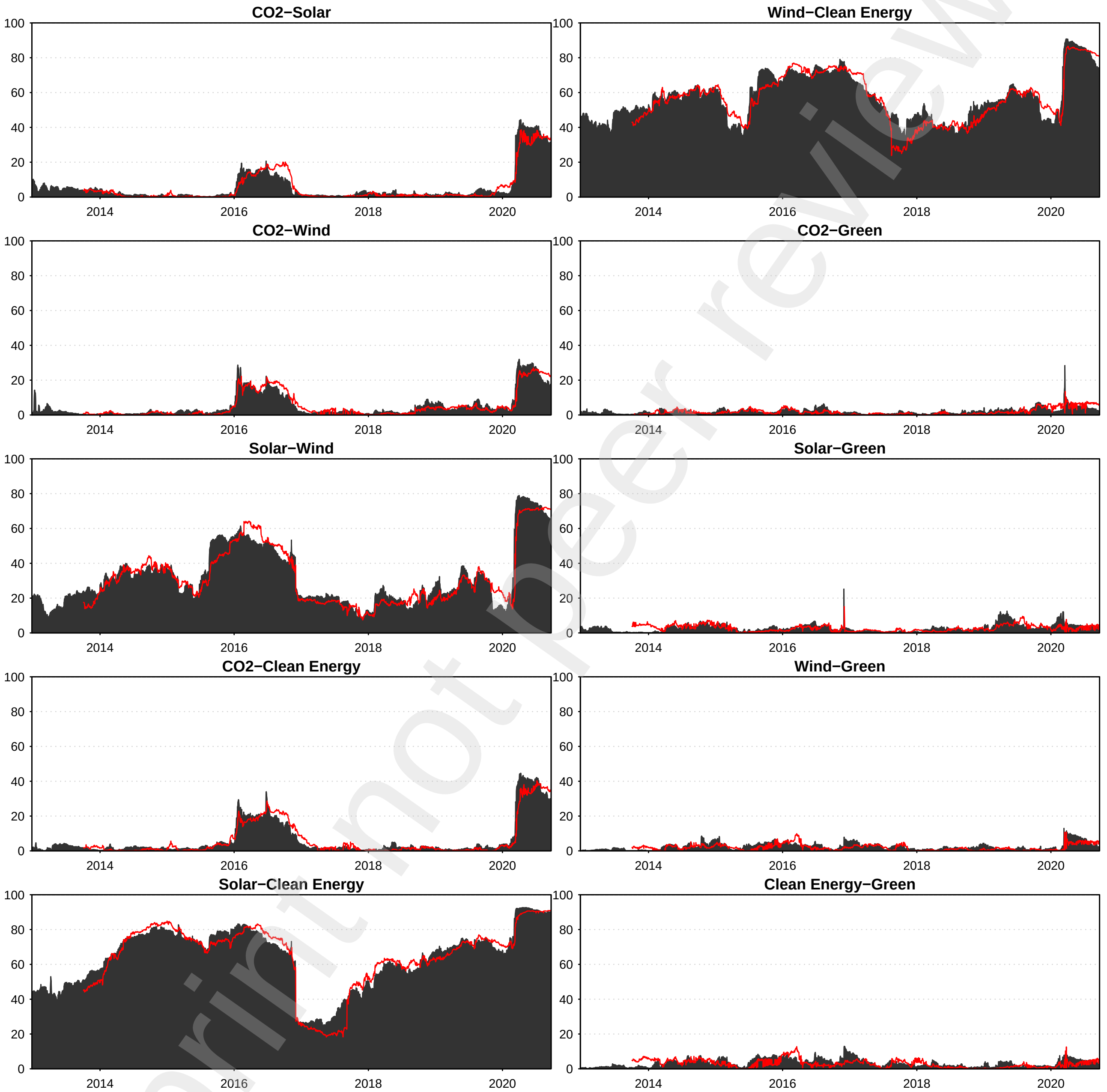
Notes: Results are based on a TVP-VAR model with lag length of order 1 (BIC) and a 20-step-ahead forecast. The black area represents the measures based upon the Antonakakis et al. (2020a) approach while the red line demonstrates the LASSO results of Gabauer et al. (2020) results.

Figure 5: Net Pairwise Directional Connectedness



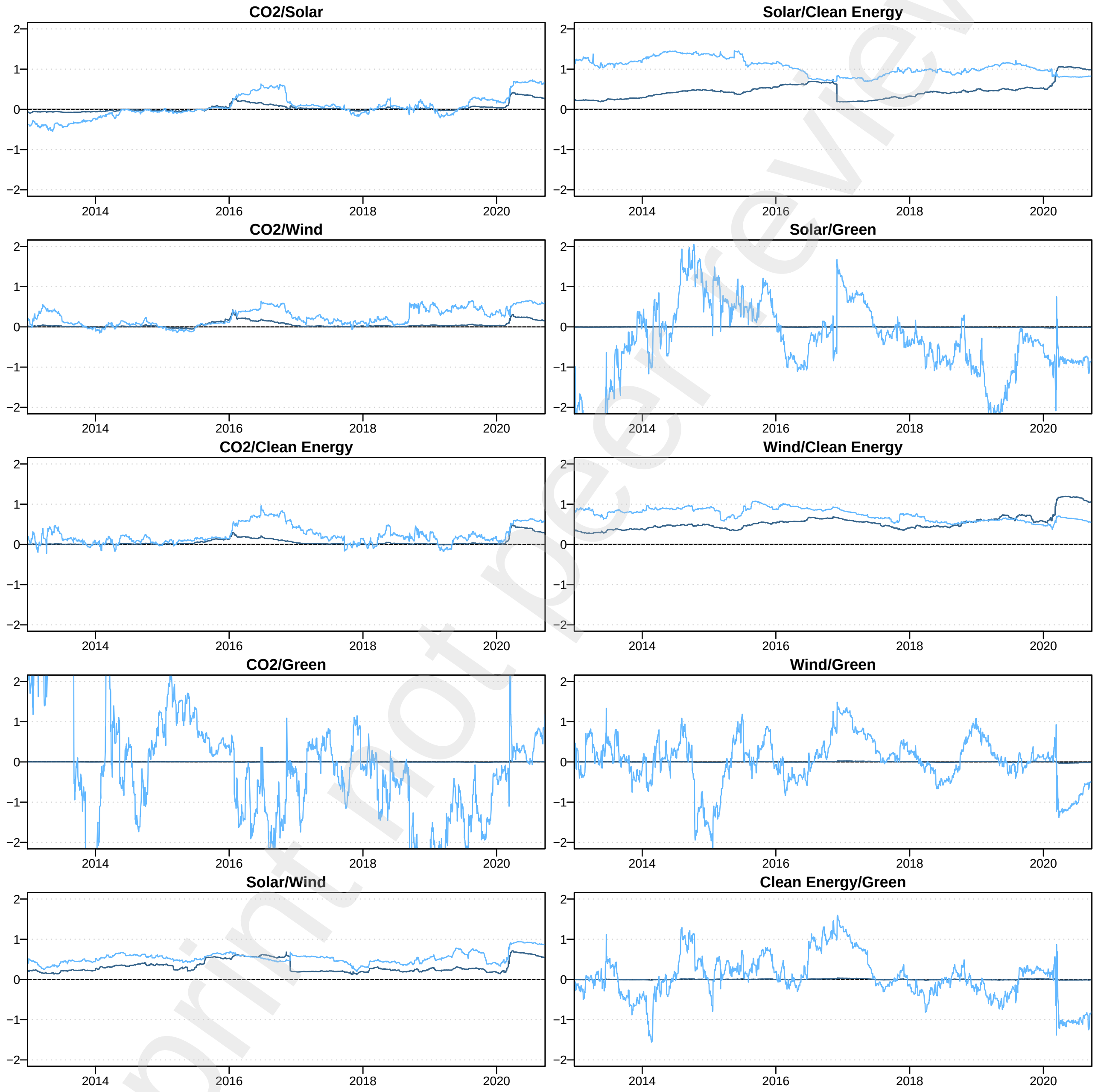
Notes: Results are based on a TVP-VAR model with lag length of order 1 (BIC) and a 20-step-ahead forecast. The black area represents the measures based upon the Antonakakis et al. (2020a) approach while the red line demonstrates the LASSO results of Gabauer et al. (2020) results.

Figure 6: Dynamic Pairwise Connectedness



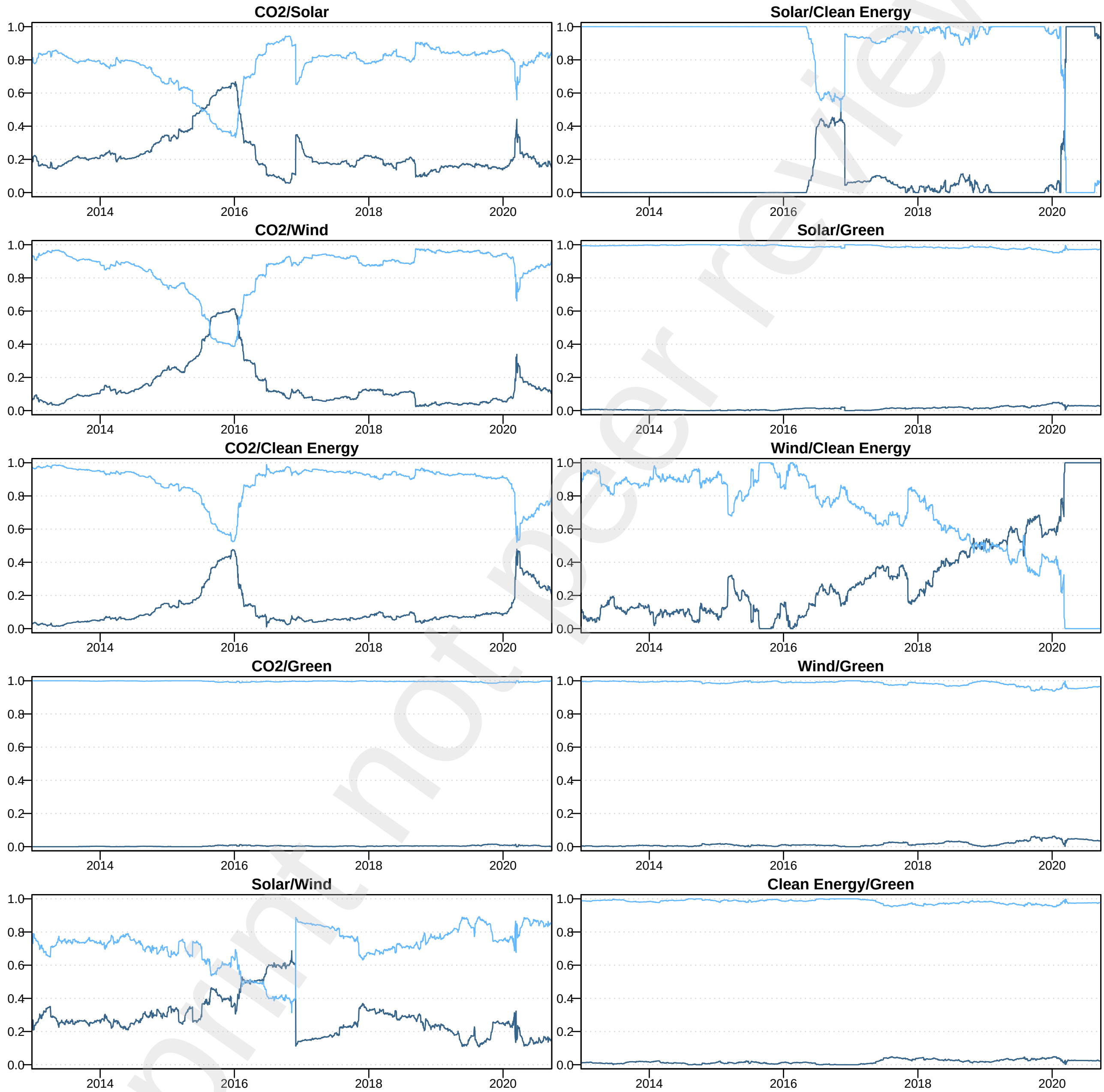
Notes: Results are based on a TVP-VAR model with lag length of order 1 (BIC) and a 20-step-ahead forecast. The black area represents the measures based upon the Antonakakis et al. (2020a) approach while the red line demonstrates the LASSO results of Gabauer et al. (2020) results.

Figure 7: Dynamic Hedge Ratios



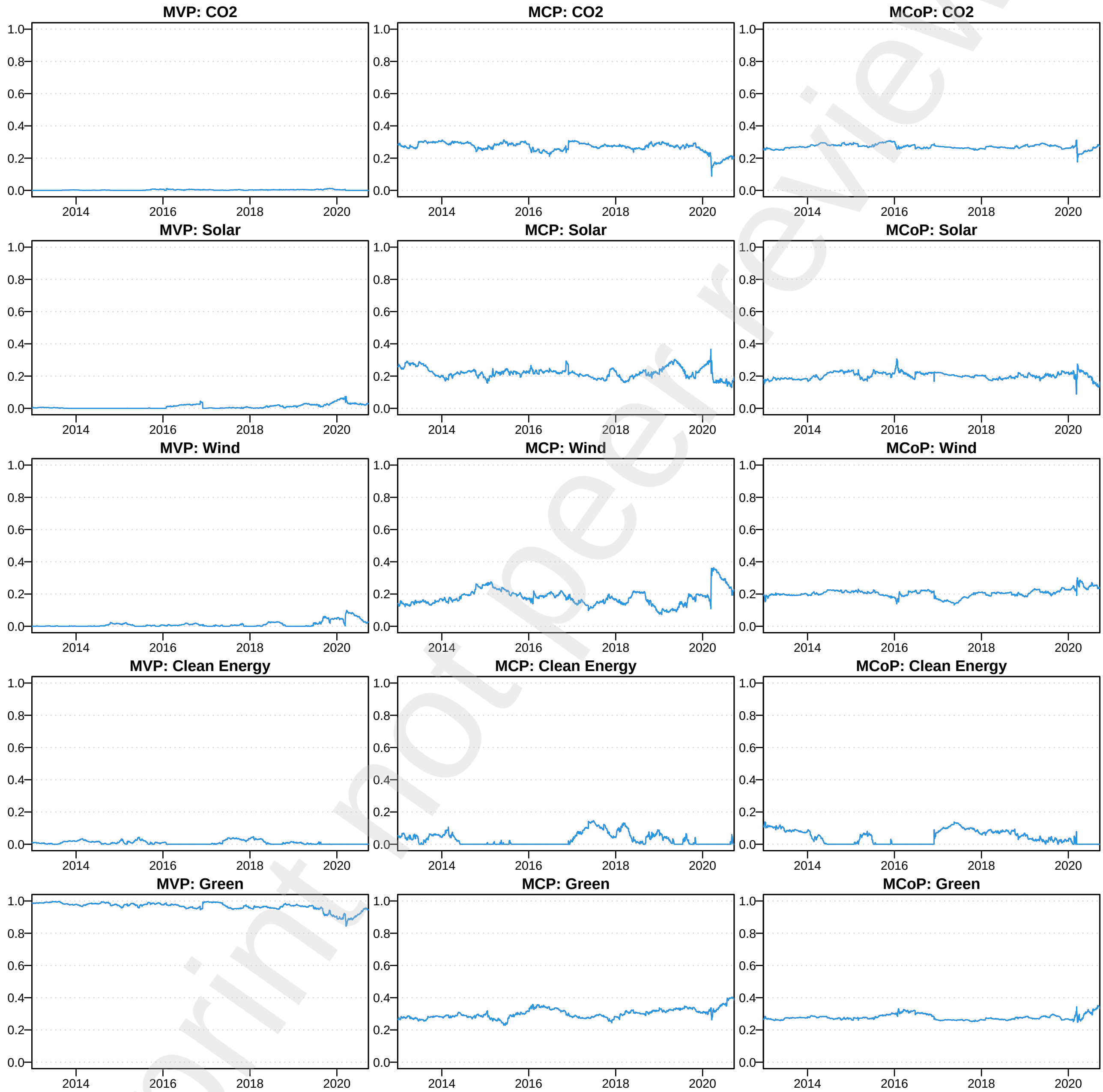
Notes: Results are based on Kroner and Sultan (1993).

Figure 8: Dynamic Bilateral Portfolio Weights



Notes: Results are based on Kroner and Ng (1998).

Figure 9: Dynamic Multivariate Portfolio Weights



Notes: Results of MVP, MCP and MCoP are based on Markovitz (1959), Christoffersen et al. (2014) and Broadstock et al. (2020), respectively.

Figure 10: Equity Line

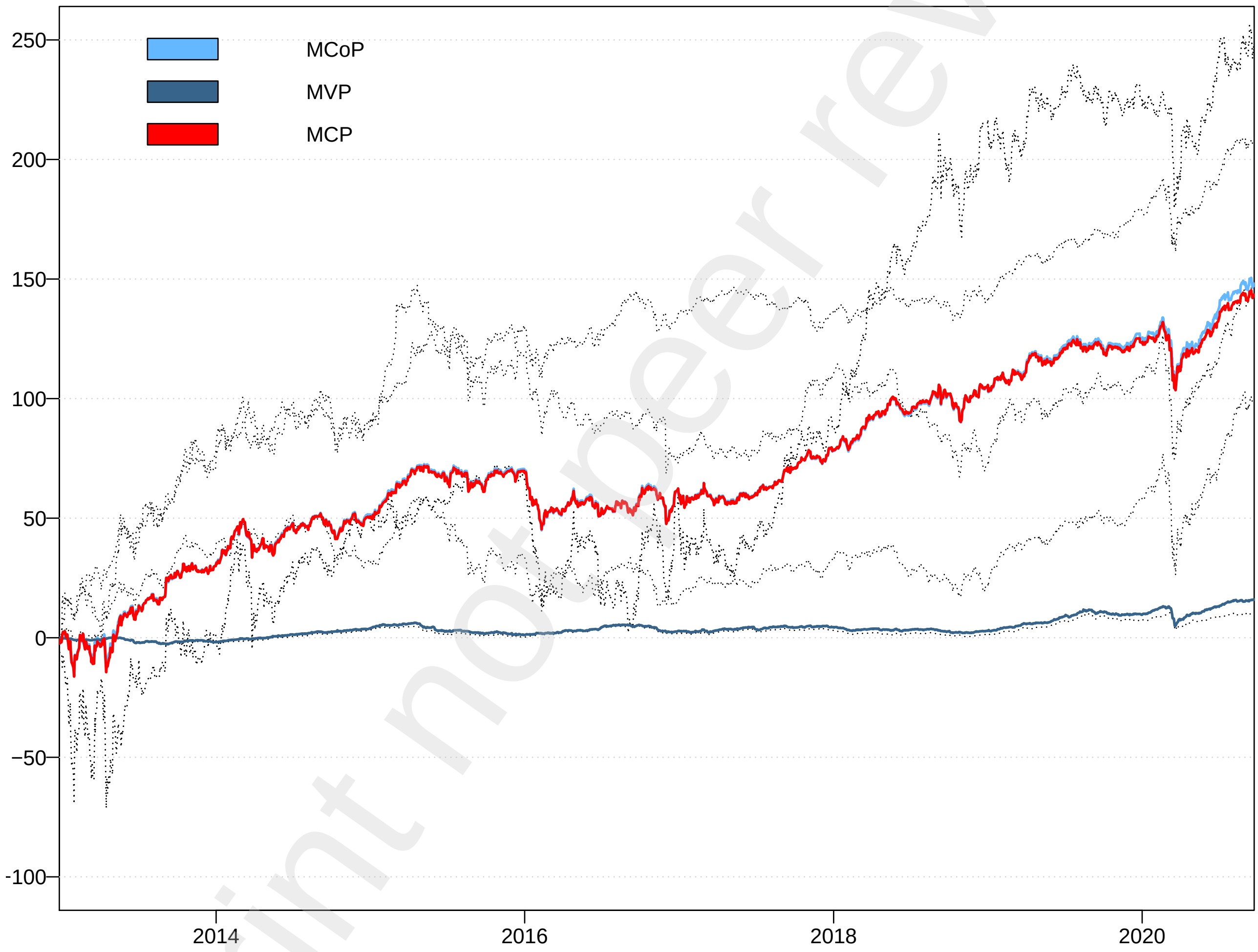


Figure 11: Equity Line After COVID-19 shock (19.03.2020)