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Role of Solar-Based Renewable Energy in Mitigating CO_2 Emissions: Evidence from Quantile-on-Quantile Estimation

Abstract

Renewable energy plays an important role in the modern economic growth paradigm. As a perpetual source, solar-based renewable energy has the ability to reduce CO_2 emissions, which has been neglected in prior empirical studies. We have analyzed the asymmetric association between solar energy consumption and CO_2 emissions in the top ten solar energy-consuming countries (Australia, Germany, Japan, Spain, Italy, USA, South Korea, UK, France, and China). Using data from 1991 to 2018, a novel methodology, 'Quantile-on-Quantile (QQ)', is applied. The results explore the mode of how quantiles of solar energy consumption asymmetrically affect the quantiles of CO_2 emissions by providing an adequate framework to comprehend the overall dependence structure. The empirical findings demonstrate that solar energy consumption reduces CO_2 emissions at different quantiles for all selected countries except France. The overall relationship is stronger at higher quantiles of CO_2 emissions for various countries. The outcomes suggest that the intensity of asymmetric relationship in solar energy-CO_2 emissions nexus differs with countries that need individual caution and attention for governments in formulating the policies connected to solar energy and the environment. Our empirical evidence also emphasizes that solar energy should be integrated for sustainable growth and environmental quality.

Keywords: Solar energy consumption (SEC); CO_2 emissions; Quantile-on-Quantile (QQ) Estimation

Jel Codes: P18; Q28; P48

1. Introduction

The world economy depends heavily on fossil fuels to satisfy the persistent energy demands, which is the primary source of greenhouse gas (GHG) emissions (Koengkan, Losekann, Fuinhas, & Marques, 2018). The carbon content of energies mix is anticipated to account for 68 percent of GHG emissions, while coal and other fossil fuels making up the remaining 32 percent (International Energy Agency, 2018). CO_2 emissions are unavoidably associated with energy consumption. In other words, economic expansion always results in CO_2 emissions in areas where traditional energy sources remain in use due to rapid industrialization, trade openness, and suburbanization. The depletion of conventional fuels, as well as their negative environmental impacts, is driving the global search for sustainable and environmentally friendly alternative energy sources (Nathaniel & Iheonu, 2019; Yurtkuran, 2021). Technology innovation has spurred efforts to replace an alternate energy source with conventional sources, and the efficiency of obtaining energy from renewable sources is always rising. Solar energy is a viable option because it is a clean, renewable, and widely available source of energy (Hereher & Kenawy, 2020; Magazzino, Mele, & Schneider, 2021). The sun provides the earth with enough energy in just 90 minutes, which is sufficient to meet the global energy demand for a whole year. Despite the fact that solar energy is abundant to this extent, it only accounts for a small portion of the world's current energy mix (Jäger-Waldau, 2020). However, this is rapidly changing, owing to global efforts to improve energy access and supply security, as well as to combat climate change (Usman, Akadiri, & Adeshola, 2020).

Solar energy is extremely inexpensive when compared to other traditional energy sources. Solar power systems can be used for a variety of purposes and are also inexpensive with respect to maintenance costs (Chen, Zhao, Lai, Wang, & Xia, 2019). The main disadvantage is that they are subject to weather fluctuations, necessitating the installation of an energy storage system, which raises the technology’s overall cost (Wilberforce et al., 2019). Between 1991 and 2020, solar energy has grown exponentially and progressed from small-scale uses to a mainstream source of electricity. Several countries have turned to solar energy generation since the development of solar cells in the 1950s. Today, China is a leading consumer of solar energy, followed by the

United States, Japan, and Germany (Jäger-Waldau, 2020). However, if we look in per capita scenario, then Australia leads in per capita solar energy consumption followed by Germany, Japan, and Spain (BP, 2019). In concentrated solar power plants, solar energy is utilized as a source of electricity for solar thermal applications (Gonzalo, Marugán, & Márquez, 2019; Wilberforce et al., 2019), solar photovoltaic (PV) plants (Ram et al., 2018; Rezk et al., 2019), photoactivated fuel cells (Li et al., 2019), hydrogen fuels (Sharma & Kolhe, 2017) and conversion of CO_2 into storable solar fuels (Xu & Carter, 2018).

Fully functional solar photovoltaic (PV) installations can now work in both urban environments and remote locations where grid connections are difficult or where there is no energy infrastructure. Solar off-grid systems can improve people's lives in rural areas by supplying electricity to education institutes and basic health care centres. In off-grid isolated rural areas, solar household systems are suggested as an affordable way of delivering power for lighting and electronics. Cooking with inefficient traditional fuel has major health and environmental consequences (i.e. indoor air pollutants, smoke and deforestation). On the other hand, solar cooking reduces the usage of fossil fuels and is the most practical application of solar energy. A solar oven saves 16.9 million tons of firewood while simultaneously reducing CO_2 emissions by 38.4 million tons annually (Machol & Rizk, 2013).

The relationship between solar energy and the environment is emphasized in two main strands of literature. The first group of studies emphasizes the positive impact of solar energy on environmental quality. For example, Raha & Pal (2010) observed that solar energy was an important source of renewable energy that could considerably reduced CO_2 emissions. Oliviera et al. (2005) argued that solar power was an encouraging alternative for traditional energy sources because it had the ability to reduce CO_2 emissions. It was observed that solar energy was more environmentally friendly than fossil fuels. Furthermore, solar panels used 99 percent less water and generated 90 percent less pollution than coal. Some recent studies also observed negative effect of renewable energy on pollution. For example, Nathaniel & Iheonu (2019) observed the impacts of renewable energy and non-renewable energy on environment for the year 1990–2014 in African countries. The empirical estimates observed that renewable energy consumption mitigated CO_2 emissions, but non-renewable energy contributed to the CO_2

emissions. Magazzino et al. (2021) evaluated the influence of solar and wind energy on CO_2 emissions in the USA, China, and India using a Machine Learning Approach. In China and the USA, solar and wind energy were found to reduce CO_2 emissions, but not significantly in the case of India. Similarly, Nathaniel & Khan (2020) and Usman et al. (2020) observed that renewable energy improved environmental quality by reducing ecological footprint in South Africa and the United States, respectively.

The second string of empirical literature presents the incredulous role of solar energy in the mitigation of CO_2 emissions. For instance, de Chalender & Benson (2019) expressed their doubts about the role of solar energy in reducing CO_2 emissions. For China, Chen et al. (2019) explored the association between renewable energy and CO_2 emissions in China for the period 1995–2012. It was found that renewable energy had a mixed impact on CO_2 emissions across different regions of China. Similarly, Parkman (2020) also argued that the installation process of solar energy was a complicated and costly process to make it on-grid. In another study, Destek & Aslan (2020) observed the association between solar energy and CO_2 emissions in G7 countries by using the data for the period 1991 to 2014. It was found that solar energy had no significant effect on CO_2 emissions. Some studies observed that the consumption of renewable energy caused an increase in CO_2 emissions (e.g. Sadorsky, 2009; Apergis & Payne 2014; Koengkan et al., 2018). Koengkan et al. (2018) calculated the effect of hydroelectricity consumption on CO_2 emissions for seven selected countries of South America for the year 1966 to 2015. It was observed that hydroelectricity consumption increased CO_2 emissions in the long run. Such divergent outcomes encourage us to examine the dynamic relationship between solar energy consumption and CO_2 emissions in greater depth.

Although the solar energy-CO_2 emissions nexus has been considered in various previous studies for different economies, no study is available for the top-10 solar energy consuming countries. This research contributes to available literature by different means. (i) Most previous studies rely on a panel data approach that delivers common findings on the solar energy-CO_2 emissions relationship, although some of the countries have no evidence of such relationship individually. On the other hand, the present study applies the advanced 'quantile-on-quantile (QQ)' method developed by Sim & Zhou (2015), which can estimate the time-series dependence in each country independently to provide global yet country-specific evidence for the relationship between variables. (ii) There are various complexities in the solar energy-environment nexus that make its estimation potentially complicated with conventional econometric methodologies (such as OLS and quantile regressions). CO_2 emissions may react differently to solar energy consumption when the solar energy consumption is in recession than when it is at its peak or boom. A large amount of solar energy consumption may have a different effect on CO_2 emissions than a small amount of solar energy consumption. (iii) Consequently, the impact of solar energy consumption on CO_2 emissions may be heterogeneous and varying when the production capacity of solar energy is different. In this context, the QQ analysis appears to be a very beneficial technique, ensuring a comprehensive estimation of the critical association between solar energy consumption and CO_2 emissions that would otherwise not be possible from the traditional methodologies. (iv) Hence, this study analyzes the asymmetric or nonlinear effects of quantiles of wind energy consumption on quantiles of CO_2 emissions, and the outcomes will explain the relationship between these variables at both the bottom and upper quantiles of the data distribution. Because of underlying dispersed features that economic indicators frequently follow an asymmetric or non-linear trajectory (Sharif, Meo, Chowdhurty, & Sohag, 2021), we suppose the asymmetric wind energy-CO_2 emissions nexus. (v) We have selected the top-10 solar energy consumer countries on the basis of per capita consumption of solar energy instead of simple consumption. Because the economic indicators in per capita form serve as direct measures of personal economic well-being (Bozoklu, Yilanci, & Gorus, 2020). The wind energy developmental dynamics of our sample countries make them feasible aspirants to be investigated in order to comprehend their wind energy role in CO_2 emissions and give additional insight into mitigation of environmental degradation. (vi) This study would be helpful for governments and policymakers to make decisions about solar energy and environment policies at different levels of solar energy production and various phases of the CO_2 emissions. It also provides valuable suggestions, which will open the routes for future research on solar energy-CO_2 emissions nexus and its implications in various countries.

The remainder of the paper is structured as follows: Section 2 explains the data set employed and its description. Section 3 defines the QQ methodology, while section 4 discusses the preliminary and main findings of the study. Finally, Section 5 concludes the study with some policy recommendations.

2. Data and its Description

For this study, our dataset consist of two variables; per capita CO_2 emissions (dependent variable) and per capita solar energy consumption (independent variable). We have examined the association between above-mentioned variables in the top ten countries[1] with the highest per capita solar energy consumption. We have selected the countries based on the per capita consumption of solar energy instead of simple consumption. Similarly, CO_2 emission is also taken in per capita form. According to Bozoklu et al. (2020), the economic indicators in per capita form serve as direct measures of personal economic well-being. Due to the availability of data, the study period ranges from the year 1991 to 2018. The data of per capita CO_2 emissions is taken from the World Development Indicators.[2] We have obtained the data for per capita solar energy consumption from British Petroleum Global.[3]

3. Methodology

3.1 Quantile Cointegration Test

Traditional cointegration tests are based on the assumption that the cointegrating vectors are constant, which may be one of the reasons that cointegration among series is not found in many cases (Chang et al., 2020). On the other hand, the quantile cointegration test presented by Xiao (2009) shows additional volatility in both explanatory and dependent variables by capturing the influence of conditional variables on the scale, position and shape of the distribution of the data and hence shows the significant extension of the traditional cointegration models (Xiao, 2009). On the basis of the traditional Engle & Granger (1987) cointegration model, Xiao (2009) introduces a new model to tackle the issue of endogeneity, which is the main drawback of traditional cointegration tests. The errors of the cointegrating equation are divided into lead-lag terms. If $\beta(\tau)$ is a vector of constants, then the special case of the model is:

$$Y_t = \alpha + \beta' Z_t + \sum_{j=-k}^{k} \Delta Z'_{t-j} \Pi_j + \mu_t \qquad \text{Eq (1)}$$

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[1] Australia, Germany, Japan, Spain, Italy, USA, South Korea, UK, France, and China

[2] https://databank.worldbank.org/source/world-development-indicators/

[3] https://www.bp.com/

and

$$Q_{\tau}^{Y}\left(Y_t / I_t^{Y} . I_t^{Z}\right) = \alpha(\tau) + \beta(\tau)' Z_t + \sum_{j=-k}^{k} \Delta Z'_{t-j} \Pi_j + F_u^{-1}(\tau) \qquad \text{Eq (2)}$$

After adding the quadratic term of the independent variable, the cointegration model can be written as follows:

$$Q_{\tau}^{Y}\left(Y_t / I_t^{Y} . I_t^{Z}\right) = \alpha(\tau) + \beta(\tau)' Z_t + \gamma(\tau)' Z_t^2 + \sum_{j=-k}^{k} \Delta Z'_{t-j} \Pi_j + \sum_{j=-k}^{k} \Delta Z_{t-j}^{2'} \Gamma_j F_u^{-1}(\tau) \qquad \text{Eq (3)}$$

The stability test of the cointegrating coefficients can be derived from equation (3) by taking the null hypothesis as H0: β (Δ) = β over all quantiles. In test statistics, a supermum rule for the absolute value of the difference $\hat{V}_n(\tau) = [\hat{\beta}(\tau) - \hat{\beta}]$ is proposed as the null hypothesis. The present paper employs the test statistic $Sup_{\tau} \left| V'_n(\tau) \right|$ across all the distributions of quantiles. The critical values of $Sup_{\tau} \left| V'_n(\tau) \right|$ test statistics are obtained by applying 1000 Monte Carlo simulations.

3.2 Quantile-on-Quantile (QQ) Regression Approach

Quantile-on-Quantile (QQ) regression approach is a novel approach for bivariate analysis. The QQ approach, which was introduced by Sim & Zhou (2015), is believed to be a mixture of conventional quantile regression (QR) and non-parametric estimation and provides richer and ample information as compared to these estimation methods and cover their deficiencies also. The QQ approach can perform well in an asymmetric environment, accounts for structural breaks and examines a comprehensive relationship between lower and upper quantiles of data series. The QQ approach provides a more realistic picture of analysis as compared to other conventional methods. The conventional quantile regression (QR) approach, which was presented by Koenker & Bassett (1978), is itself considered to be an extended form of classical regression model but more comprehensive in a sense that it measures the impact of an independent variable not only on the center of the dependent variable but also at its tails. The conventional QR approach is unable to find the complete dependency among the variables. Although it considers heterogeneity in the relationship, it occasionally ignores the role of uncertainty in estimating the association between independent and dependent variables.

There are many advantages of the quantile regression (QR) approach, like its suitability for the models with heteroscedasticity. Its estimators are not susceptible to outliers, therefore, they are more robust, and it efficiently uses time and cross-sectional data to increase the variability of data and reduces multicollinearity. Despite having a lot of merits, the quantile regression technique has a serious limitation as it is ineffective to depict the complete dependence of variables. Therefore in such a case, econometricians suggest using the OLS technique presented by Stone (1977) and Cleveland (1979), which considers the local effect of the quantiles of an explanatory variable on the explained variable. As an alternative, the use of local linear regression prevents the only problem of non-parametric estimation that is "the curse of dimensionality". It determines the local regression around each data point in the sample by allocating more weighting to the immediate neighbor. Thus by combing the use of both the above-mentioned approaches, we can evaluate the association between different quantiles of the dependent and independent variables. Therefore, this study used Quantile-on-Quantile (QQ) framework to recognize convolutions in the solar energy-CO_2 emissions nexus that would be challenging to estimate by using any other traditional approach like OLS or traditional quantile regression (QR).

Our basic model, in its original form, can be constituted by the following model of non-parametric quantile regression:

$$CO_{2t} = \beta^{\theta} (SEC_t) + \mu_t^{\theta} \qquad \text{Eq (4)}$$

Here, CO_{2t} represents the carbon dioxide emissions in period t. SEC_t is solar energy consumption in time t. θ denotes the θth quantile of the conditional distribution of CO_2 emissions. μ_t^{θ} is quantile error term, and its conditional θth quantile is supposed to be zero. As we have a lack of prior knowledge about the association between SEC_t and CO_{2t}, so $\beta^{\theta}(.)$ is assumed to be an unknown function.

To examine equation 4, the local linear regression is used in the neighborhood of SEC^{τ} as follows:

$$\beta^{\theta}(SEC_t) \approx \beta^{\theta}(SEC^{\tau}) + \beta^{\theta'}(SEC^{\tau})\,(SEC_t - SEC^{\tau}) \qquad \text{Eq.(5)}$$

In equation 5, $\beta^{\theta'}$ illustrates the partial derivative of $\beta^{\theta}(SEC_t)$ with respect to SEC_t, defined as the partial effect. $\beta^{\theta}(SEC^{\tau})$ and $\beta^{\theta'}(SEC^{\tau})$ in equation 5 are functions of θ and τ. Moreover, $\beta^{\theta}(SEC^{\tau})$ can be represented by $\beta_0(\theta,\tau)$ while $\beta^{\theta'}(SEC^{\tau})$ can be denoted by $\beta_1(\theta,\tau)$. Accordingly, the revised form of equation 5 can be expressed as follows:

$$\beta^{\theta}(SEC_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)\,(SEC_t - SEC^{\tau}) \qquad \text{Eq.(6)}$$

Now by substituting equation 6 into equation 4, we get equation 7 for Quantile-on-Quantile (QQ) methodology as follows:

$$CO_{2t} = \underbrace{\beta_0(\theta,\tau) + \beta_1(\theta,\tau)\left(SEC_t - \mathrm{SEC}^{\tau}\right)}_{(*)} + u_t^{\theta} \qquad \text{Eq.(7)}$$

Equation 7 shows the functional form of QQ technique. The part (*) shows the θth conditional quantile of the CO_2. Equation 7 represents the true impact of θth quantile of SEC on τth quantile of CO_2. β_0 and β_1 are parameters, which are doubly indexed in θ and τ, define the quantile association between SEC and CO_2. The values of β_0 and β_1 may vary depending on the values of the quantiles of dependent and independent variables. The overall structure of dependence between the independent and dependent variables is established in equation 7 by connecting their respective distributions.

We have included only one dependent variable (CO_2) and one independent variable (SEC) in the functional form of the QQ model (equation 7) because the QQ approach is a bivariate regression approach that does not allow the inclusion of other control variables in the model along with SEC. Hence we have ignored some important factors that can affect the SEC-CO_2 nexus by causing the negative effects of the production, installation, and recycling process of solar energy systems on CO_2. Although having bivariate properties, the QQ approach is superior to other traditional time series techniques. It can estimate the asymmetric effects of quantiles of the independent variable on the quantiles of the dependent variable at both the bottom and top quantiles of the data distribution and thus gives more detailed and robust results than other old methodologies (Shahzad et al., 2020).

The selection of bandwidth (h) is very important in the non-parametric QQ estimation. Bandwidth is used in the minimization problem, which captures the effect of trade openness on economic growth, as shown in equation 8.

$$Min_{\delta_0 \delta_1} \sum_{t=1}^{n} \sigma_{\phi}[\mathrm{CO}_{2t} - \delta_0 - \delta_1(\mathrm{SEC}_t - SEC^{\tau})]L[\frac{M_n(\mathrm{SEN}_t) - \tau}{h}] \qquad \text{Eq.(8)}$$

Here, σ_{ϕ} denotes the quantile loss function. L (.) represents the Gaussian kernel function, which is used as minimal weighting criteria to improve the efficiency of estimation. It gives weight to the observations in the neighborhood of SEC^{τ}. h represents the bandwidth parameter of the Gaussian kernel function. The Gaussian kernel allocates more weights to nearer observations, and it is symmetrical around zero. Particularly, in this study, the weights of the Gaussian kernel are inversely correlated to the distance between the empirical distribution function of SEC_t, represented by $M_n(\mathrm{SEC}_t) = \frac{1}{n}\sum_{k=1}^{n} I(\mathrm{SEC}_k < SEC_t)$, and the value of the distribution function that corresponds to the quantile SEC_t, is denoted by τ ,while I is the usual indicator function.

Bandwidth in kernel regression works as a smoothing parameter because it controls bias and variance in the output. A large bandwidth leads to biased estimation, while a small bandwidth creates a higher value of variance (Sim & Zhou, 2015). So, balancing between bias and variance is crucial. Hence, we choose 5 percent (h=0.05) as a bandwidth parameter for the quantile distribution of our study, followed by the works of Sim & Zhou (2015) and Shahbaz et al. (2018).[4]

3.3 Validity of QQ Approach

The QQ technique can decompose the traditional QR model by enabling specific estimates for various quantiles of the independent variable. For our study, the QR approach can estimate the θth quantile of SEC on CO_2, and hence the quantile parameters are only indexed by θ. On the other hand, the QQ approach regresses θth quantile of SEC on τth quantile of CO_2, and, hence, its quantile parameters are indexed by both θ and τ, which leads to more disaggregated information than the QR model. Due to this decomposition property of the QQ approach, the

[4] A variety of alternative bandwidth values have also been checked. The outcomes of the estimation, however, remain qualitatively similar.

estimates of the traditional QR approach can be recovered from the QQ estimates. Hence, the QR parameters indexed by θ can be obtained by taking a simple average of the QQ parameters along τ. For instance, the slope coefficient of the QR model, which calculates the effect of SEC on various quantiles of CO_2 and is represented by $\gamma_1(\theta)$, can be generated as follows:

$$\gamma_1(\theta) \equiv \bar{\hat{\beta}}_1 = \frac{1}{s}\sum_{\tau} \hat{\beta}_1(\theta,\tau) \qquad \text{Eq.(9)}$$

Where τ= [0.05, 0.10,…,0.95] and S = 19 is the number of quantiles.

In this context, by comparing the estimated QR parameters with the τ-averaged QQ parameters, we can verify the validity of the QQ regression approach.

4 Results and Discussion

This section is reserved for presenting the preliminary and main findings of the results along with a detailed discussion.

4.1 Preliminary Findings

A descriptive statistics analysis for per capita solar energy consumption (SEC) and per capita CO_2 emissions (CO_2) is presented in Table1.

Table 1: Descriptive Statistics for SEC and CO_2

Variables	Mean	Max.	Min.	Std. Dev.	J-B Stats	ADF Level	ADFΔ
Panel A: Solar Energy Consumption (KW per capita)							
Australia	253.71	402.65	5.28	163.89	4.67*	-0.89	-6.17*
Germany	196.80	552.24	4.72	208.26	30.60*	-2.10	-3.50**
Japan	169.20	307.76	1.30	125.66	1.79*	-1.37	-4.25*
Spain	116.18	491.51	2.78	151.20	7.30	-1.71	-3.65**
Italy	91.49	522.40	0.43	151.61	14.75*	-1.27	-4.27*
USA	57.50	187.20	1.65	60.45	2.19*	-1.52	-5.68*
South Korea	38.13	288.78	1.59	76.26	40.65*	-1.78	-6.19*
UK	18.88	127.27	0.49	36.99	15.50*	-1.95	-5.61*

France	12.06	28.67	0.79	9.41	3.65*	-1.32	-5.64*
China	9.47	26.85	0.49	8.24	7.72*	-1.65	-4.80*
Panel B: CO_2 Emissions (metric ton per capita)							
Australia	16.98	18.20	15.33	0.95	4.40*	-1.56	-4.41*
Germany	9.48	10.36	8.10	0.49	5.90*	-1.72	-7.68*
Japan	9.45	9.88	8.63	0.31	4.90*	-2.14	-5.72*
Spain	6.40	8.09	5.03	1.20	1.60*	-1.97	-3.97*
Italy	6.44	7.60	5.27	0.77	0.24*	-1.62	-3.95*
USA	18.52	20.17	15.49	1.45	4.95*	-5.69*	-6.23*
South Korea	11.28	12.11	4.54	0.90	1.57*	-1.90	-3.73**
UK	7.60	9.20	5.03	1.90	1.69*	-1.68	-4.46*
France	5.36	6.14	4.59	0.56	1.63*	-1.83	-4.12*
China	26.28	70.03	2.14	25.83	6.76*	-1.54	-5.72*

Note:* and ** show the significance level at 1% and 5%, respectively.

Australia uses the highest magnitude of SEC with the mean value for SEC (253.73) kilowatt (KW) per capita, which varies from 5.28 to 402.65. Germany is on the second number with the mean value for SEC of (196.80) KW per capita, which ranges from 4.72 to 552.24. Japan and Spain are in third and fourth place with mean values of SEC of 169.20 and 116.28 KW per capita, respectively. If we look on CO_2 then China has a highly polluted economy with a mean value of (26.28) metric ton of CO_2, which ranges from 2.14 to 70.03. USA is in second place with a mean value of (18.52) metric ton per capita of CO_2, ranging from 15.49 to 20.17. Australia and South Korea are in third and fourth place with mean values of CO_2, ranging from 16.98 and 15.33 metric ton per capita, respectively. The highly significant values of the Jarque-Bera test indicate that both SEC and CO_2 have not been normally distributed in selected countries except for Spain, where SEC has a normal distribution. The non-normal distribution of data in our sample countries explicates the rationality of the quantile-on-quantile (QQ) regression, which is robust for such kind of data (Shahzad et al., 2020). The Augmented Dickey-Fuller (ADF) unit root test reveals that most variables are non-stationary at level, but they become stationary at their first differences. So, we have used stationary data for the empirical analysis by transforming SEC and CO_2 into their first differences, followed by Shahbaz, Zakaria, Shahzad, & Mahalik (2018) and Shahzad et al. (2020).

Table 2: Correlation between SEC and CO_2

Countries	Correlation	t-Stats	p-value
Australia	-0.89	-12.78*	0.00
Germany	-0.67	-8.60*	0.00
Japan	-0.53	-2.90*	0.00
Spain	-0.68	-8.91*	0.00
Italy	-0.74	-9.37*	0.00
USA	-0.87	-28.35*	0.00
South Korea	-0.74	-4.03*	0.00
UK	-0.78	-5.40*	0.00
France	0.88	13.30*	0.00
China	-0.74	-4.12*	0.00

Note:'*' shows the significance level at 1%.

Correlation coefficients of our variables in Table-2 indicate that SEC and CO_2 are significantly interlinked with each other for all sample economies. Australia has the highest correlation value of (-0.89), followed by France (-0.88), the USA (-0.87) and the UK (-0.78). It is implied that SEC and CO_2 are negatively linked with each other except in France.

4.2 Main Findings

Table 3 shows the results of the quantile cointegration test for each country. **τ** shows the **τth** quantile of per capita solar energy consumption (SEC). The stability of the parameters is demonstrated by the supremum norm values of coefficients (β and γ), which are extracted from equation (3).

Table3: Quantile Cointegration Test Results (SEC and CO_2)

Country	Coefficient	$Sup_\tau \lvert V_n(\tau) \rvert$	CV1	CV5	CV10
Australia SEC vs. CO_2	β	1245.74	937.79	547.09	208.70
	γ	786.87	588.96	499.95	375.74
Germany SEC vs. CO_2	β	6237.65	5688.96	4679.53	3780.78
	γ	3270.90	2693.75	2187.70	1857.47
Japan SEC vs. CO_2	β	3930.90	3765.25	246.50	204.98
	γ	162.78	158.86	47.07	45.79
Spain SEC vs. CO_2	β	7113.35	3495.10	3085.16	2226.37
	γ	605.43	300.87	213.18	118.10

Italy SEC vs. CO_2	β	1836.77	1547.79	1042.74	994.85
	γ	949.76	686.63	496.74	345.86
USA SEC vs. CO_2	β	8312.21	5286.20	3137.05	2524.35
	γ	176.60	105.39	50.84	39.30
South Korea SEC vs. CO_2	β	8755.50	6732.00	4771.12	1478.86
	γ	398.17	200.62	100.05	96.05
UK SEC vs. CO_2	β	9080.01	7001.09	5504.75	2220.00
	γ	260.68	168.40	129.57	95.10
France SEC vs. CO_2	β	8550.57	6532.00	4871.12	1278.86
	γ	399.18	201.62	105.07	95.05
China SEC vs. CO_2	β	68590.30	58367.30	57308.24	54888.75
	γ	2456.61	1494.23	1449.41	1431.18

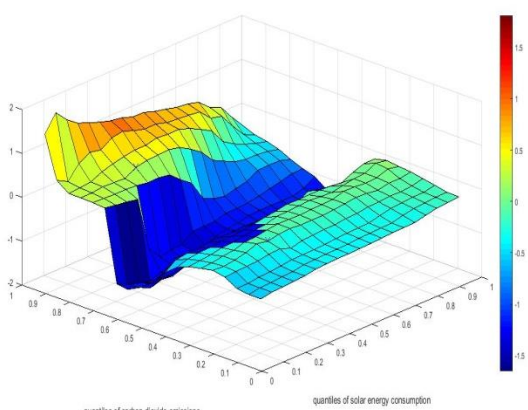
Note: The t-statistic for quantile cointegration is obtained by applying an equally spaced grid of 19 quantiles (0.05-0.95). Supremum norm estimates of the parameters (β and γ) are also given while their critical values at 1, 5, and 10 percent level of significance are represented by CV1, CV5, and CV10, respectively.

The outcomes of the quantile cointegration test for each country confirms that the cointegration relationship between SEC and CO_2 changes over the quantile distribution. It is observed that all the coefficients (β and γ) have larger supremum norm values compare to all the critical values, which indicate the sign of a significant asymmetric or nonlinear long-run relationship between SEC and CO_2 in selected countries.

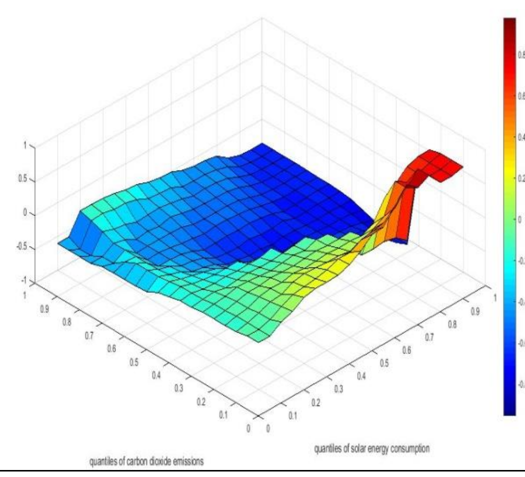
Figure 1: Quantile-on-Quantile (QQ) estimates of the slope coefficient, $\boldsymbol{\beta}_1(\boldsymbol{\theta}, \boldsymbol{\tau})$

Impact of Solar Energy Consumption on CO_2 emissions

i).Australia

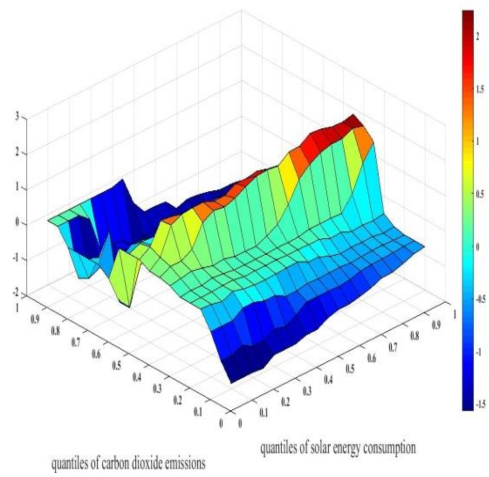


ii). Germany

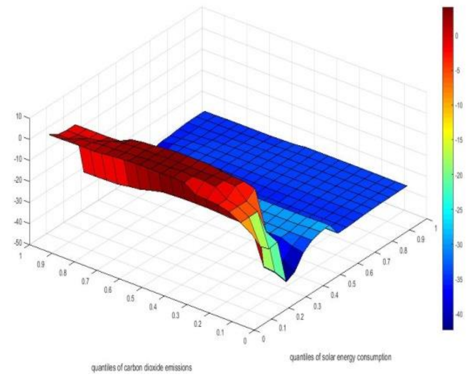


iii).Japan

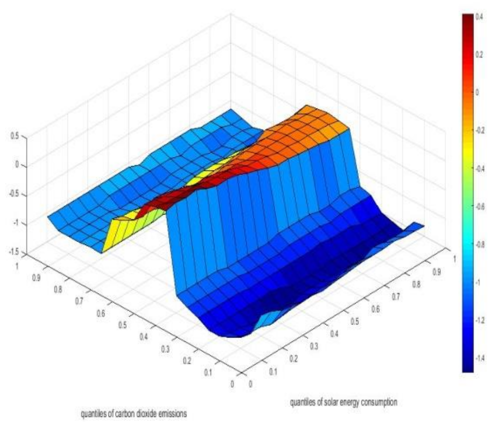
iv).Spain



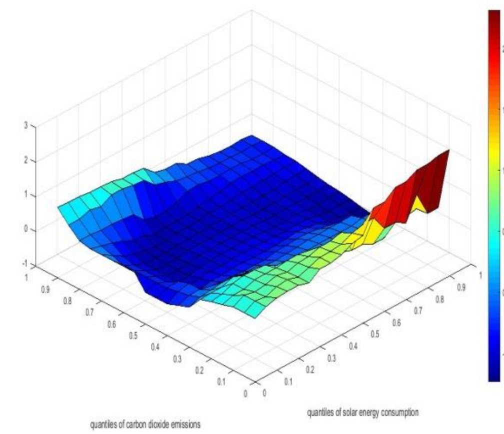
v).Italy



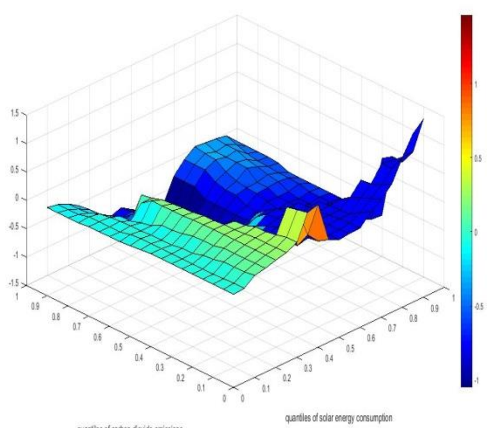
vi).USA



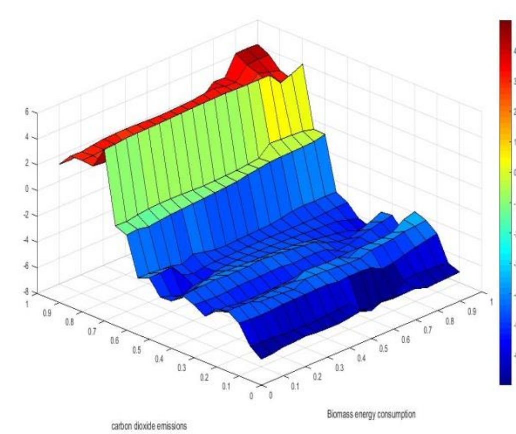
vii). South Korea



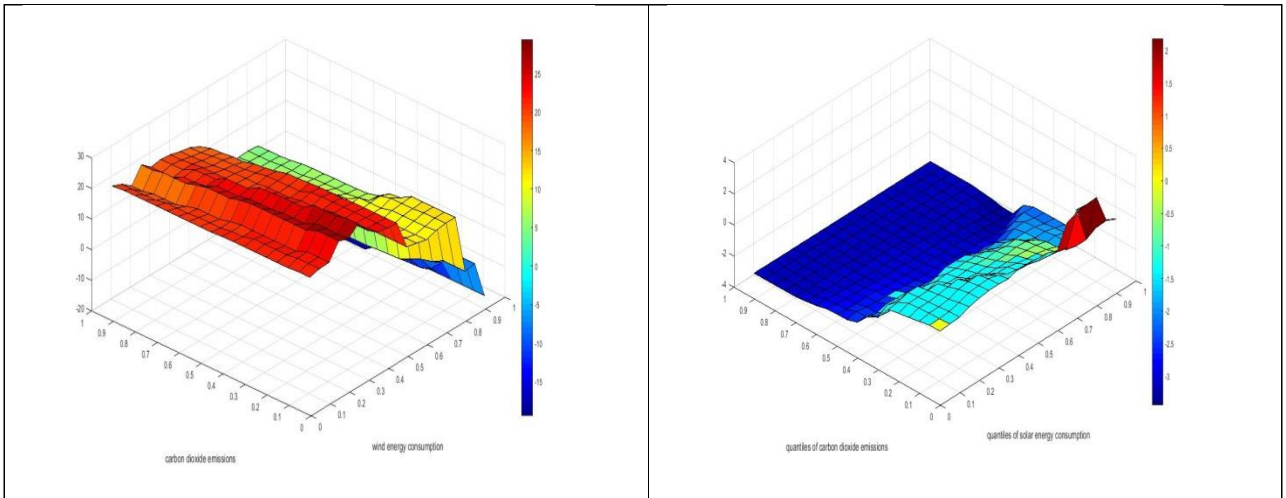
viii).UK



ix).France



x).China



Note: The estimates of the slope coefficient $\beta_1(\theta,\tau)$ are demonstrated on the z-axis against the quantiles of solar energy consumption (SEC) on the x-axis and the quantiles of CO_2 emissions on the y-axis.

Figure-1 shows the slope estimates $\beta_1(\boldsymbol{\theta}, \boldsymbol{\tau})$, which possess the impact of $\boldsymbol{\theta}$**th** quantile of SEC on $\boldsymbol{\tau}$th quantile of CO_2 by different values of $\boldsymbol{\theta}$ and $\boldsymbol{\tau}$ for the top-10 solar energy consuming countries. For **Australia**, a weak and negative relationship is found in the regions which incorporate all the quantiles of SEC with bottom to medium and higher quantiles of CO_2 (0.05-0.45 and 0.80-0.95). It means that there is no significant association between SEC and CO_2. This outcome may be explained by the severely limited weight of energy consumption in Australia and is consistent with the previous finding of Destek & Aslan (2020) and Parkman (2020), who also reported an insignificant association between SEC and CO_2. However, this relationship becomes strong between the regions, which combine all the quantiles of SEC with medium to medium-high quantiles of CO_2 (0.50-0.75). In **Germany**, a substantial and negative association is found between the regions, which connect all the quantiles of SEC (0.05-0.95) with lower-middle to upper quantiles of CO_2 (0.45-0.95). However, the association becomes weak between the lower to lower-middle quantiles of CO_2 (0.05-0.45) and all the quantiles of SEC.

In **Japan**, all the quantiles of SEC have a strong negative association with the lower and upper quantiles of CO_2 (0.05-0.20 and 0.85-0.95). It postulates that SEC improves environmental quality by reducing CO_2 during both periods of low and high emissions. This association becomes weak between the regions, which connect all the quantiles of SEC with lower-middle quantiles of CO_2 (0.25-0.40). However, this association turns into positive in the middle quantiles of CO_2 (0.45-0.55). The positive link between SEC and CO_2 shows that solar energy degrades environmental quality by enhancing pollution during the period of moderate CO_2. In **Spain**, a strong negative relationship between SEC and CO_2 is observed in the regions, which combine the lower-middle to higher quantiles of SEC (0.45-0.95) with the link across all the quantiles of CO_2 (0.05-0.95). This particularly pronounced negative connection during increasing solar energy consumption suggests that SEC causes significant mitigation in CO_2 in Spain when the consumption of solar energy has an upward trend. However, a strong positive solar energy-CO_2 association is observed between the areas which correlate the lower quantiles of SEC (0.05-0.35) with all the quantiles of CO_2. It postulates that SEC degrades environmental quality by increasing CO_2 during periods of low SEC in Spain.

In **Italy**, a strong negative relationship between SEC and CO_2 emissions is observed in the regions, which combine all the quantiles of SEC (0.05-0.95) with the link across lower to middle quantiles (0.05-0.50) and higher quantiles (0.80-0.95) of CO_2. This particularly pronounced negative connection in times of lower and higher levels of CO_2 recommends that solar energy serves as a relevant engine of improving environmental quality by reducing CO_2 for Italy during the periods of both downturn and upsurge of CO_2. However, a strong positive association is also found in the middle quantiles of CO_2, which defines that solar energy increases pollution during the period of moderate CO_2. In **China** and **the USA,** the quantiles of SEC have a strong negative association with the lower-middle to higher-quantiles of CO_2 (i.e., 0.40-0.95). There is a weak negative association between the areas which combine the bottom quantiles of SEC with lower-middle quantiles of CO_2 (0.05-0.35). The finding suggests that the consumption of solar energy acts as a source of improving environmental quality by reducing the amount of CO_2 in China and the USA during both downturns and hike in CO_2.

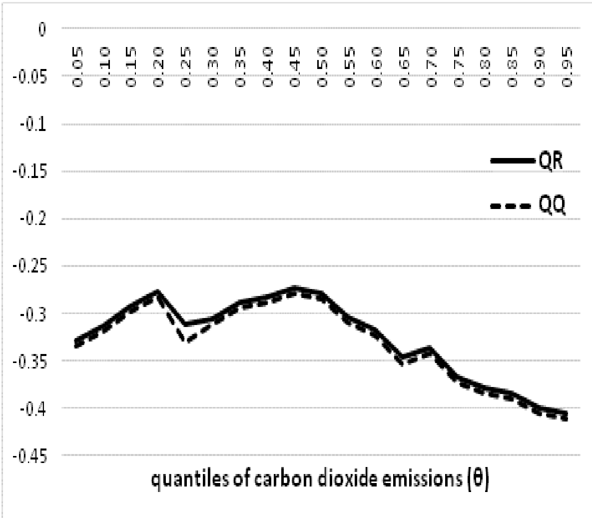
In **South Korea**, a vigorous and negative relationship between SEC and CO_2 is observed in the regions, which combine the upper-middle to higher quantiles of SEC (0.60-0.95) with the link across all the quantiles of CO_2 (0.05-0.95). This particularly pronounced negative connection during higher SEC suggests that SEC causes a significant reduction in CO_2 in South Korea during periods characterized by higher SEC and hence improves environmental quality. A weak negative solar energy-CO_2 emissions association is observed between the areas which correlate the lower to lower-middle quantiles of SEC (0.05-0.45) with all the quantiles of CO_2, which postulates that SEC has an insignificant association with CO_2 during the periods of low SEC. In **UK,** the negative impact of SEC is dominant. The quantiles of SEC have a negative and strong association with the lower to upper-middle quantiles of CO_2 (i.e., 0.04-0.70). The result suggests that SEC appears to have an encouraging effect on environmental quality through reducing CO_2, principally during periods of healthy SEC. However, this negative effect is weak between the areas, which correlate the quantiles of SEC with the upper-middle quantiles of CO_2 (0.75-0.80). However, the top quantiles of CO_2 are positively correlated with all the quantiles of SEC.

Contrast to the above findings, the impact of SEC on CO_2 in France is mixed. A strong positive impact of SEC on CO_2 is observed between the regions which combine lower to middle quantiles of SEC (i.e., 0.05-0.50) with all the quantiles of CO_2 (0.05-0.95). A weak negative SEC-CO_2 nexus is found between the areas which correlate the upper-middle quantiles (0.55-75) of the SEC with all the quantiles of CO_2. However, the SEC on its top quantiles (0.85-0.95) has a strong negative association with all the quantiles of CO_2. This particularly pronounced positive connection during the boom of the economy in the form of high SEC suggests that SEC causes a further increase in CO_2 in these countries during periods characterized by higher SEC.

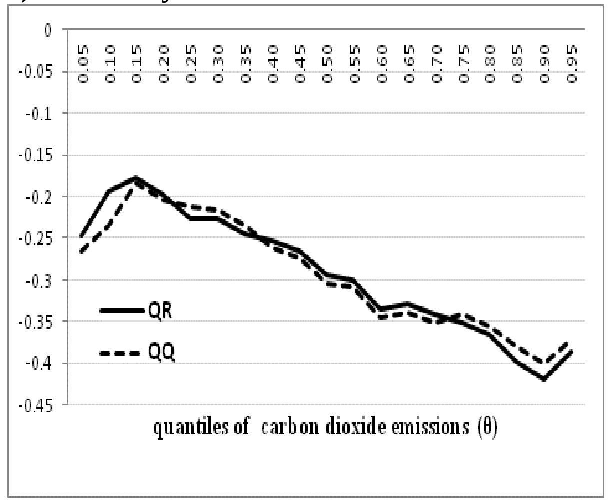
The findings of the QQ approach can be explored to see if the results are similar or not to those of the QR approach. Figure-2 validates our previous findings of the QQ approach. The graphs indicate that the average quantile-on-quantile (QQ) regression estimates of the slope coefficients have approximately the same behavior as quantile regression (QR) estimates for all selected countries.

Figure 2: Checking the Validity of QQ Approach by Comparing QR and QQ Regression Estimates

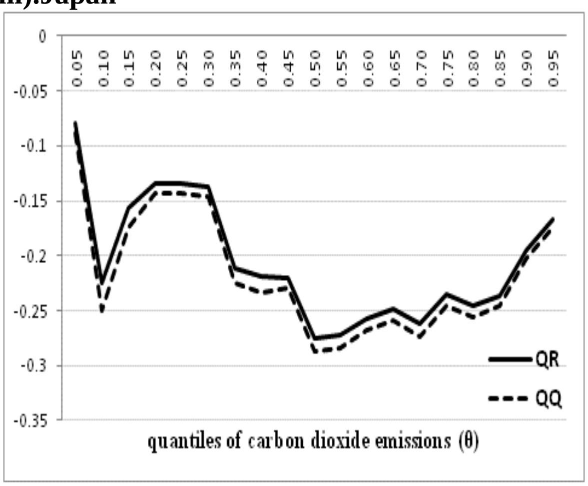
i).Australia



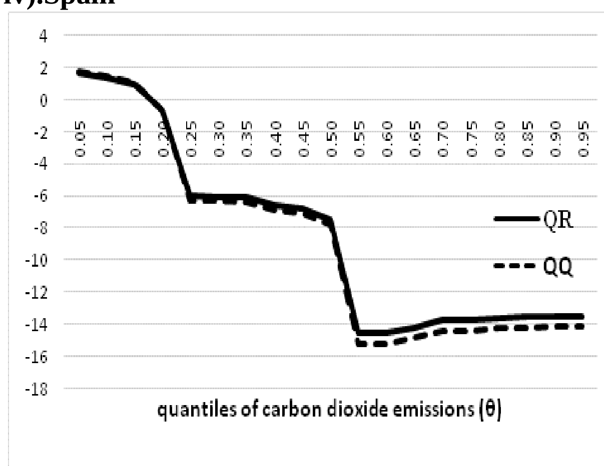
ii). Germany



iii).Japan

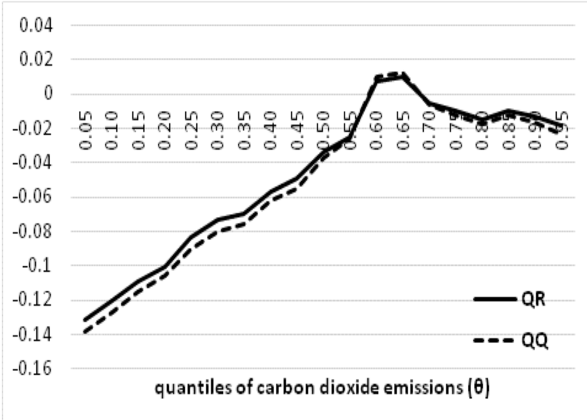


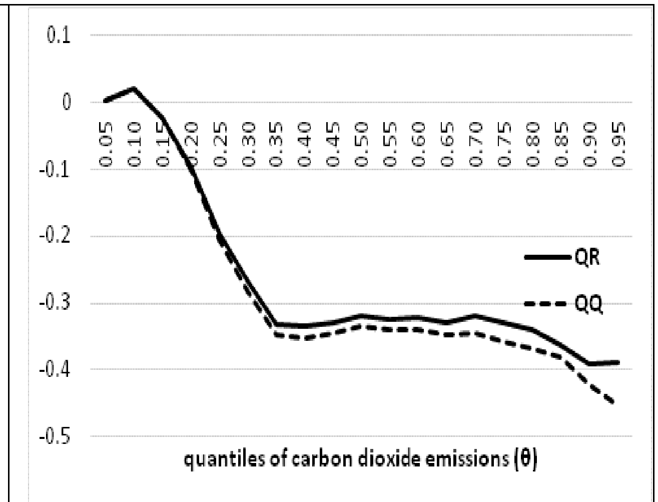
iv).Spain



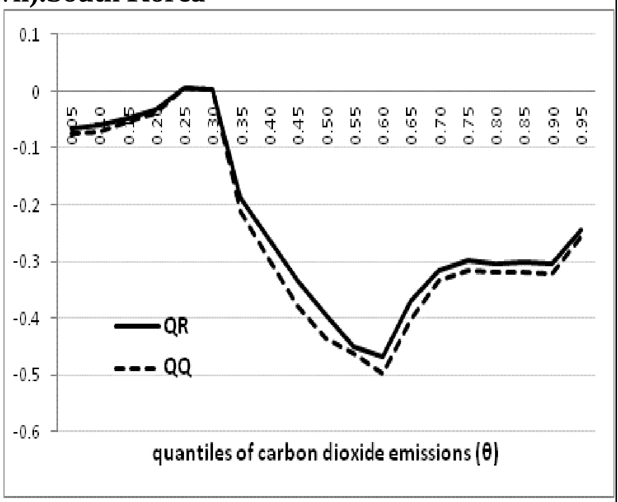
v). Italy

vi).USA

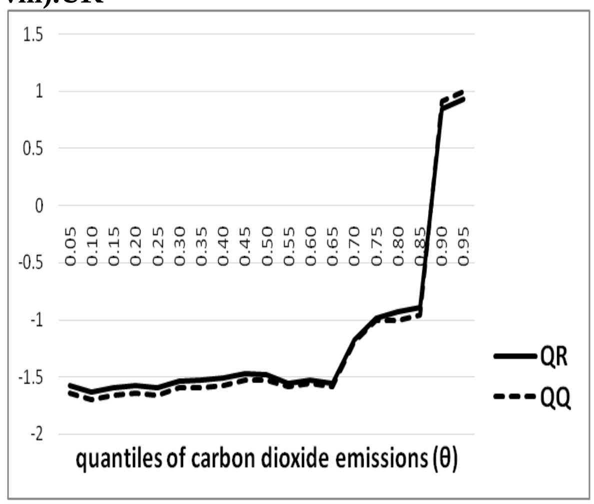




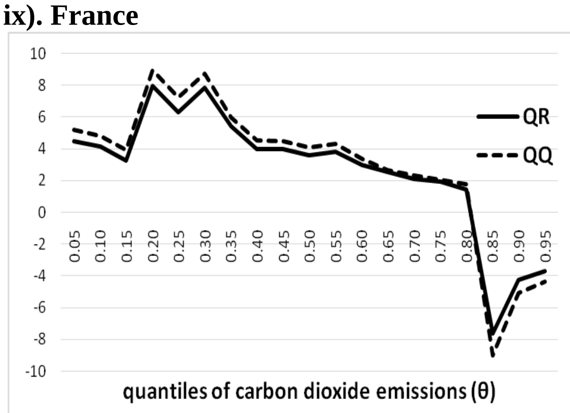
vii).South Korea



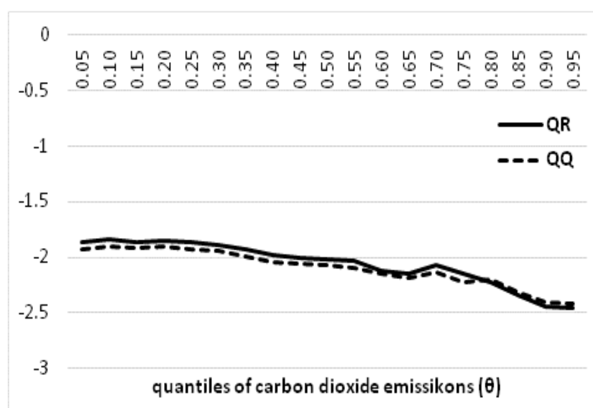
viii).UK



ix). France



x).China



Note: The estimates of the traditional quantile regression (QR) parameters and the averaged quantile-on-quantile (QQ) parameters are shown at various quantiles of CO_2 emissions.

Figure 2 indicates that Australia, Germany, Japan, Spain, Italy, USA, South Korea, UK, and China show a negative association between SEC and CO_2. On the other hand, the mixed relationship is found in the case of France. Furthermore, our findings indicate the presence of heterogeneity between SEC and CO_2 in all selected countries. According to the size of coefficients, the effect of SEC on CO_2 is comparatively larger in France and Spain. However, relatively low efficiency of SEC is observed in the case of Italy.

4.3 Discussion

Overall, the findings reveal a negative association between SEC and CO_2 in the majority of selected countries. The negative impact of WEC on CO_2 is dominant in nine (i.e., Australia, Germany, Japan, Spain, Italy, USA, South Korea, UK, and China) out of ten selected economies, which recommends that by utilizing CO_2 as an environmental indicator, SEC improves environmental quality in these countries. We have observed that solar energy is an effective strategy for reducing CO_2. Our empirical findings back up our proposition and a number of previous studies, like Oliviera et al. (2005) and Nathaniel & Iheonu (2019), which shows the optimistic role of solar-based renewable energy in mitigating pollution. Our findings also support the study of Pehl et al. (2017), who found that solar energy had a substantially lower carbon footprint during its life cycle than gas or coal. The observation of significant and negative coefficients for SEC supports a recent COP21 energy day policy argument emphasizing the necessity of reducing barriers to renewable energy growth. There is a concern that the production of solar panels is linked to large reductions in emissions in the recent year as a result of technological innovations. The findings are partially consistent with Usman et al. (2020) and Magazzino et al. (2021), who found that renewable (solar) energy was inversely correlated with CO_2 in the USA and China, respectively. In France, a mixed relationship is observed between SEC and CO_2, which is due to specific conditions like growth patterns, technology, business cycles, and population. This outcome is also aligning with the empirical study of Chen et al. (2019), who found a mixed relationship between renewable energy and CO_2 emissions in different regions of China. Despite the fact that solar-based renewable energy is significantly less polluting than other conventional energies, the manufacturing method for solar PV systems generates toxic materials that can contribute to CO_2. The ability to produce solar energy also relies on the levels of expertise and technology employed during the production process. The favorable impact of solar-based renewable energy on CO_2 is also attributable to the lack of financial incentives, which discourage the development of solar energy technology and, as a result, green energy consumption. Other possible reasons for the positive association between the significant number of quantiles of SEC and CO_2 are legal and institutional hurdles that dissuaded the expansion of solar energy technology, as well as increased usage of other renewable energy sources (i.e. wind and hydroelectricity) in some countries.

For a variety of reasons, the effect of sun energy slightly changes across the sample and between quantiles. Higher quantiles of CO_2, for example, are more profound in a negative association with the SEC (i.e. for China, the USA, Italy, and UK), which can be explained by the fact that a high amount of CO_2 exchanges fossil fuel with renewable (solar) energy. As a result, such a shift in energy mix aids in the reduction of CO_2, easing the burden on nature in terms of CO_2 absorption. The heterogeneity in the impact of SEC among countries is may be due to the different economic situations (i.e. population, technology, and economic growth patterns) of our sample countries. Neglecting this kind of country heterogeneity may result in incorrect conclusions. In each country, the slope coefficient varies across different quantiles of SEC and CO_2. The findings also indicate that the relationship between SEC and CO_2 is not consistent across the top and bottom quantiles of the data distribution and is depends on the magnitude and sign of shocks, as well as the particular stage of the business cycle that impacts SEC.

5 Conclusion and Policy Recommendations

We have analyzed the asymmetric association between SEC and CO_2 in the top ten per capita solar energy-consuming countries (Australia, Germany, Japan, Spain, Italy, USA, South Korea, UK, France, and China). Using data from 1991 to 2018, a novel methodology, ‘Quantile-on-Quantile (QQ)’, is applied. The results explore the mode of how quantiles of SEC asymmetrically affect the quantiles of CO_2 by providing an adequate framework to comprehend the overall dependence structure. The empirical findings demonstrate that SEC reduces CO_2 at different quantiles for all selected countries except France.

It is a global priority to reduce the negative externalities of human economic activities. Clean energy, according to proponents, is a necessary mitigation approach for reducing negative externalities while retaining significant economic growth. The observation of significant and negative coefficients for SEC also supports a recent policy arguments made by the Paris Agreement (2016) and Sustainable Development Goals (2015), which recommend the elimination of obstacles to clean energy growth, including solar energy.

Governments must strengthen the notion of environmental protection and reduction of CO_2 emissions with the help of various platforms such as television, internet, and radio so that more families and individuals realize the importance of pollution control. Governments must develop and enforce emission reduction policies and energy conservation, as well as attach corresponding measures to encourage production units to implement green technologies and severely punish those who violate them. Subsidies for nonrenewable energies should be gradually phased out or transferred to renewable energy technologies to encourage the usage of renewable energy sources, especially solar energy. Moreover, subsidies for renewable energy technologies benefit the environment, enhance incentives for investment in green technologies, and promote competitiveness by lowering their price relative to nonrenewable energy sources.

Low-interest loans are essential for the installation of solar energy systems. Governments and banking institutions should provide low-interest loans to their clients to purchase solar panels. Many homeowners in the United States, for example, have financed the construction of solar photovoltaic (PV) systems with low-interest loans (4–5%). Hence, many people are interested in installing solar PV panels. These days, net-metering programs allow PV owners to reduce their electricity bills by receiving compensations for electricity usage and power generated by the solar system. Through the net-metering method, households and small businesses can sell excess electricity generated by their PV systems to conventional electricity providers at a reasonable price in exchange for a credit on their utility bills.

Sometimes, solar energy system produces CO_2 emissions in the environment due to the use of hazardous materials in the production process of PV solar panels. PV producers employ poisonous substances, explosive gases, and caustic liquids in their manufacturing processes. The presence and amount of these components vary depending on the cell type. Many manufacturers use lead in the layer of cell metallization for wafer-based silicon modules. Cadmium telluride

(CdTe) solar cells are made up of cadmium (Cd) and copper indium selenide (CIS), while many other types of solar cells contain selenium. All of these materials are hazardous and cause CO_2 emissions. As a result, it is critical to employ stringent control systems that decrease CO_2 emissions from hazardous materials in module production processes.

Finally, the results above are valid for the limited data of one environmental indicator used in this study. Therefore, further empirical studies are needed to analyze the solar energy-environment nexus by including some more environmental indicators like N_2O emissions, CH_4 emissions, and ecological footprint. Further research work is recommended by taking other renewable energy sources like wind energy and hydroelectricity. Another main constraint of the present study is the application of the bivariate QQ regression approach in which we are not incorporating other control variables, which may affect the influence of SEC on CO_2 emissions. In future studies, the model can be extended by applying some multivariate quantile approaches (i.e., Quantile ARDL) that help the interpretation of the nexus over a larger number of independent variables.

Availability of Data:-

The data that support the findings of this study are available on request from the corresponding author.

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