**Does Globalization Endorse Renewable Energy Consumption in presence of economic activity, oil prices and carbon emissions? A Quantile Analysis of 30 OECD countries**

**Or**

**Robust globalization(s) and Renewable energy consumption in OECD countries**

**Abstract.** This study examines the impact of globalization(s) on renewable energy consumption for OECD countries by endonizing per capita GDP, oil prices and per capita carbon emissions. We use the robust globalization(s) measured by the “classic”, “reconstructed” and “revisited” globalization indexes. The novel method of Machado and Silva Panel quantile regression (2018) approach is used to obtain robust findings for the renewable energy consumption-globalization nexus. The results confirm the presence of a long-run association between renewable energy consumption with globalization(s), per capita GDP, oil prices and per capita carbon emissions. The empirical results also describe that there are positive effects for per capita income, the real price of oil and carbon emissions per capita on the renewable energy consumption. In addition, a higher level of globalization (overall, economics, social and political) promotes renewable energy consumption, while the “reconstructed” and “revisited” economic globalization reduces the use of renewable energy consumption, and this finding is also robust to different measures of economic globalization. Moreover, the panel quantile regression reveals that renewable energy consumption increases the domestic economy in the middle (0.50) quantile group of the population through importing more advanced technology and positive spilling over markets, while the lower quantile group and higher quantile group of the population are using non-renewable (coal, wood) energy because of the livelihood practice that is based on coal and wood (lower quantiles group of the population) and for the sake of speedy growth (higher quantiles group of the population) that worsens the environmental quality without caring for the contents of globalization.

**Keywords**: renewable energy consumption; globalization(s); OECD economies

**JEL** Codes: Q42; Q41; F64; C33

**1. Introduction**

Renewable energy consumption is the main driver for economic growth in the Organization of Economic Cooperation and Development (OECD) countries. According to International Energy Agency (IEA, 2020)[[1]](#footnote-2), renewable energy provides a comprehensive picture of historical and current markets tends for OECD countries. It gives a new insight to overview renewable energy consumption and waste in the world since 1990s. In 2018, the share of renewable energy supply to total energy is 13.5% for OECD countries which is higher than others region. Further, the annual growth rate of renewable energy increase to 3.2% in 2000-2018 from 1.7% in 1990-2000. But, the share of renewable energy drastically increases from 3.1% in 1990 to 35.7% in 2018. The higher growth rate of renewable energy was observed because of increasing share of solar energy (40.1%), wind (19.9%), liquid biofuels (16.7%), biogas (8%) and solar thermal energy (5.6%) respectively. Moreover, the OECD countries use renewable energy for transport sector from the last three decades to protect the environmental quality. Given concern about carbon emissions, climate change and global warming, the OECD countries have emphasised more on diversifying the energy mix and securing energy supply. This interest towards energy supported by heterogeneous government policies[[2]](#footnote-3) open a market for renewable energy consumption globally. Therefore, we are motivated to examine the impact of globalization(s) on renewable energy consumption for the case of 30 OECD countries.

The novelty or contribution of the paper is that we use different pattern of globalization(s) of Konjunkturforschungsstelle (KOF; 2018). First, this is the first study where we use the classic globalization(s)[[3]](#footnote-4), reconstructed economic globalization(s)[[4]](#footnote-5) and finally the revisited economic globalization(s)[[5]](#footnote-6)and their impact on renewable energy consumption. Second, we use the novel method of Machado and Silva Panel quantile regression (2018)[[6]](#footnote-7) approach to analyse the relationship between globalization(s) and renewable energy consumption and aim to obtain robust findings for the energy-globalization nexus. This quantile regression gives more explicit results than ordinary least square method because, first, it captures individual heterogeneity and distributional heterogeneity that are neglected by ordinary least square method (Zhu et *al.,* 2016; Cheng et *al.,* 2018, 2019; Yan et *al.,* 2019). Second, this method describes the entire conditional distribution of the dependent variable. Third, it gives not only one solution to each quantile but also robust outlying observation of the exogenous variables (Damette and Delacote, 2012; Flores et *al.,* 2014; Yaduma et *al.,* 2015; Zhu et *al.,* 2016).

Further, it is necessary to understand the main components and factors of renewable energy consumption due to the issues on climate change and global warming. According to (Omri and Nguyen, 2014), the demand for renewable energy consumption would rise for future globally. Indeed, according to Shahbaz et *al.,* (2016, 2018a, and 2018b), globalization(s) can have both positive and negative impact on energy consumption. According to Rahman and Miah (2017), globalization impact negatively on energy consumption for 26 developing countries. After, new economic policy, 1991, globalization make a change for human lives of the world and their socio-economic and political factors through giving more important on foreign direct investment, capital flows and international relation in term of trade. According to Dreher (2006), for enhancing economic performance in the long-run, higher degree of globalization is necessary in developing and developed economies. Further, the degree of globalization not only makes better performance of economic structure but also modifies the nature of energy consumption (Shahbaz et *al.,* 2016). Therefore, this change energy consumption can be decreased or increased depend on the pattern of globalization(s). Globalization and its relationship with energy consumption are well addressed in *“Pollution haven hypothesis[[7]](#footnote-8)”.* This impact of globalization can be realized through international activities and foreign direct investment (Eskeland and Harrison, 2003; Bu et *al.,* 2016).

Indeed, higher degree of investment is required in technology for shape the renewable energy consumption by foreign firm. In addition, both import and export can provide the better inputs to renewable energy consumption. In short, the developed countries or OECD countries desire to use the low carbon energy generating sources such as renewable energy sources by implementing higher level of technology, trade openness. At this stage, the OECD countries focus on the globalization(s) on environmental quality rather than on the economic performance since they use less-carbon dioxide-emitting energy sources in the production processes. In addition, we use the control variables such as per capita income, the real oil price, and the level of carbon dioxide emissions in the relationship between the pattern of globalization(s) and its impact on renewable energy consumption to obtain the robust empirical findings. We use real gross domestic product (GDP) because as income increases energy consumption also increases, it shows that GDP also considers as a factor may impact on renewable energy consumption. The oil prices affect the renewable energy via fossil fuels. Moreover, the carbon emissions also use a factor effecting renewable energy consumption (Omri and Nguyen, 2014). We use these set of control variables as per the literature based on Cheng et *al.,* (2018; 2019); Gozgor (2018); Sarkodie and Adams (2018).

The remainder of the paper is organized as follows. Section 2 explains the related literature on the determinants of renewable energy as well as the relationship between the energy demand and the levels of nuanced globalization. Section 3 reviews the Theoretical Framework on Renewable energy. Section 4 provides the data with the empirical models and explains the econometric methodology used in the empirical analysis. Section 5 reports the empirical findings as well as discusses. Section 6 provides the conclusion and policy implications.

**2. Review of related studies**

*2.1. Economic growth and Renewable energy consumption nexus*

According to Sener et *al.,* (2018), the interest in the literature related to the drivers of renewable energy deployment for countries had been relatively weak until 2010.[[8]](#footnote-9) With the Kyoto Protocol's first commitment, the increasing crude oil prices, and the volatility of traditional energy prices have led to an increase in the interest on the topic. A fast-developing strand of the literature examines the relationship between renewable energy consumption and economic growth (Apergis and Payne, 2010a and 2010b; Lin and Moubarak, 2014; Alper and Oguz, 2016; Bhattacharya et *al.,*2016;). However, those studies do not have a consensus on the direction and the magnitude of the relationship as they have used different data sets, time periods and methodologies. Compared to studies on the renewable energy-growth nexus, the determinants of renewable energy consumption is a new research field. In one of the earliest studies, Sadorsky (2009a) analyzes the determinants of the renewable energy in the G7 countries using panel cointegration techniques. That study finds that real GDP per capita and the per capita carbon dioxide emissions are the main drivers of the renewable energy consumption in the long-run, while the oil price has a negative but a relatively smaller impact. In a subsequent study, Sadorsky (2009b) shows that real per capita income has a positive effect on per capita renewable energy consumption in 18 emerging economies by using panel cointegration, and the evidence is in line with Sadorsky (2009a). This implies that higher economic growth is a key factor in terms of increasing the share of renewable energy in total energy consumption. Salim and Rafiq (2012) analyze the determinants of renewable energy consumption in Brazil, China, India, Indonesia, the Philippines, and Turkey. They show that in renewable energy consumption is influenced by the income and pollutant emissions in Brazil, China, India, and Indonesia. However, per capita income is the only determinant of the renewable energy demand in the Philippines and Turkey in the long-run. In line with the previous studies, Salim and Rafiq (2012) also observe that the crude oil price has a negative impact on renewable energy consumption. Destek and Sinha (2020), found the inverted U-shaped relationship between renewable energy consumption and economic growth in 24 OECD countries. Further, according to Belaid and Zrelli, (2019) for 9 Mediterranean countries, Rahman and Velayutham, (2020) for South Asia, Razmi, et *al.,* (2020); 130 developing countries, Fan and Hao (2020); for chines provinces and Chen and Stengos (2020) for Iran found that economic growth positively impacts on renewable energy consumption in long-run. Alam and Murad (2020) also found that economic growth promotes renewable energy consumption in the long-run and adverse effect in the short-run for 25 OECD countries.

*2.2. CO2 emissions and Renewable energy consumption linkages*

Further, Marques et *al.,* (2010) show that the lobby of the traditional energy sources, the energy self-sufficiency, the carbon dioxide emissions, and the per capita income are important determinants of the renewable energy demand in 24 European countries. Omri and Nguyen (2014) examine the determinants of the renewable energy consumption in 64 countries and find that per capita carbon dioxide emissions have a positive effect on the renewable energy consumption. In a comprehensive study, Aguirre and Ibikunle (2014) illustrate that carbon dioxide emissions, energy consumption, GDP per capita, ratification of the Kyoto protocol, high electricity usage rates in the industry sector are the fundamental drivers of renewable energy growth in 38 countries. Paramati et *al.,* (2016) found that carbon dioxide emissions have a negative impact on renewable energy demand in 20 emerging market economies. Chen (2018) shows that there is a positive relationship between economic development and renewable energy consumption. In addition, the level of carbon dioxide emissions, per capita exports, per capita imports, and changes in the urbanization also explain the renewable energy consumption at the different Chinese regions. Moreover, Dong et *al.,* (2018a, 2018b) and Yu et *al.,* (2020), found that renewable energy consumption reduces the carbon emissions in China. Akram et *al.,* (2020) for developing countries, Destek and Aslan, (2020) for G-7 countries and Liu et *al.,* (2020) for UK economy also found that renewable energy consumption reduces the carbon emissions. Cheng et *al.,* (2020), found that reducing the cost of carbon emissions increases the renewable energy consumption for the case of China. Indeed, for the case of California, Virginia and Dublin, Xu and Buyya, (2020) found that the usage of carbon emission can be reduced through renewable energy consumption at varied power plants at different locations.

*2.3. Oil prices and Renewable energy consumption relationship*

According to Gourevitch (1978); Ikenberry (1986); and Geller et *al.,* (2006), oil prices as a measure component to impact on different energy consumption. As oil prices increase, the demand for energy increase via technological innovation and reducing carbon emissions costs. For the relationship between real oil prices and renewable energy consumption, the most noticeable literature are Henriques and Sadorsky (2008), Broadstock et *al.,* (2012), Sadorsky (2012b), Wen et *al.,* (2014), Inchauspe et *al.,* (2015), Reboredo, (2015); Reboredo et *al.,* (2017); Shah et *al.,* (2018); and Kyritsis and Serletis, (2019). Apergis and Payne, (2015) find the long-run relationship between real oil prices and renewable energy for South America. Cheon and Urpelainen, (2012) found that oil prices increase the renewable energy consumption through technological innovation. According to Nilsson, (2019) and Hsiaoet *al.,* (2019) the oil prices have a positive and significant impact on renewable energy consumption through innovation of new technology.

*2.4. Globalization(s)-Energy consumption relationship*

Indeed, globalization enables countries to decrease the energy consumption by importing technology into the energy consumption and production activities (Baek et *al.,* 2009). Economic globalization, which enhances the level of technology, increases the productivity in energy sources (i.e., energy-saving) and decreases the cost of energy. At this stage, the impact of trade openness, as a benchmark indicator of economic globalization, on energy demand has been investigated in the energy economics literature. For example, Baek et *al.,* (2009), Copeland and Taylor (1994), Lean and Smyth (2010), Ozturk and Acaravci (2013), and Shahbaz et *al.,* (2013) find that the trade openness decreases the energy consumption by providing the use of imported technology and stimulating the environmental quality. However, according to Copeland (2005), trade openness increases the per capita energy consumption. In addition, Aissa et *al.,* (2014) and Narayan and Smyth (2009) find the validity of the neutral hypothesis (no significant relationship) between the exports (main indicator of economic globalization) and the energy consumption in the Middle East and North Africa countries and the African countries, respectively. Furthermore, Dedeoglu and Kaya (2013) and Sadorsky (2011 and 2012a) observe the validity of the feedback effect (bidirectional causality) between the exports (main indicator of economic globalization) and the energy consumption in the long-run. Finally, there is the mixed evidence in the literature. For instance, Shahbaz et *al.,* (2014) examine the causal linkage between the energy consumption and the trade openness in 91 low-income, the middle-income, and the high-income economies. The authors find the U-shaped relationship between energy consumption and trade openness in the low- and middle-income countries, but there is an “inverted U-shaped” relationship between the related variables in the high-income economies.

There are only a few studies that have used the KOF globalization index of Dreher (2006). For example, Shahbaz et *al.,* (2016) examine the effects of globalization indexes of Dreher (2006) on energy consumption in India. The authors find that the level of globalization reduces energy consumption through the channels of energy efficiency and less carbon dioxide-emitting technologies. Further, Shahbaz et *al.,* (2018a) demonstrate that globalization increases energy consumption in most of the developed countries using techniques that validated the globalization-driven energy consumption hypothesis. However, there is a negative relationship between the related variables in the case of the United Kingdom and the United States. Moreover, Shahbaz et *al.,* (2018b) find that globalization promotes energy consumption in Ireland and the Netherlands. To conclude the literature review, the relationship the energy consumption and the globalization are found to be mixed at best. The usage of the narrowly defined economic globalization (e.g. exports, imports, FDI, and trade openness) and the different econometric techniques are among the main reasons for the mixed findings. Kutan et *al.,* (2018) confirm the positive relationship between FDI on renewable energy consumption in BRICS countries. Moreover, Gozgor et *al.,* (2020) found that globalization positively impact on renewable energy consumption. As per the given literature, researchers have taken globalization such as trade openness, FDI, export, import but none of the studies have highlighted different pattern of globalization and their impact on renewable energy consumption. Therefore, by conducting this research, we are able to fulfil the gap.

**3. Theoretical Framework on Renewable energy**

This section explains the theoretical setting of renewable energy consumption which is based on Rafiq and Alam (2010) renewable energy consumption factors determinants in the emerging economies and Sardosky (2009a) seminal work that is based on renewable energy consumption in G7 economies. According to the theoretical understanding, a standard approach on renewable energy consumption can be postulated while we associate with its price and gross domestic product (Masih and Masih, 1997; Narayan and Singh 2007). There are two approach of renewable energy consumption, first, demand side approach of renewable energy consumption started by J.M. Keynes in 1936 that is based on macroeconomics growth framework on the demand for goods and services. By focusing on Keynes theory, the demand side approach implies the effective demand and consumption that determine the output level. Its major issues are that the effective demand is generated by the government, the households and the business men; it is not based on the free market set up. This theory is mainly applied to analysis the relationship between energy prices, renewable energy consumption and gross domestic product into a energy demand model (Masih and Masih, 1997; Asafu-Adjaye, 2000; Lee, 2005; Narayan and Singh 2007; Ruhul et *al.,* 2008; Rafiq and Salim, 2009; Sadorsky, 2009b). Moreover, Ang (2007, 2008) inserts the pollutant emissions as a variable to link between energy demand and economic activities. But later on, Aug’s study is not considered as demand side approach due to lack of energy prices.

Second, according to the supply side approach of the renewable energy consumption, the growth of the economy can be effectively fostered through capital investment, flexible tax reduction and dwindling regulation. Based on the supply side approach, individuals will gain from high production supply with minimizing the costs that will raise the level of employment. This concept also suggests that production supply is a major component of economic growth that explains demand and consumption are a subordinate consequence. This theory also shows that tax reduction in a particular economy set up enhances the economic growth by motivating save, invest and work. Finally, it evaluates energy use (renewable and non-renewable) in standard production function economic activities (Oh and Lee, 2004; Ghali and El-Sakka, 2004; Soytas and Sari 2007).

**4. Data, Model and Methodology**

***4.1. Data***

We work with panel data[[9]](#footnote-10) covering the period 1970-2015 for 30 OECD countries[[10]](#footnote-11). It includes total renewable energy consumption in million tonnes oil equivalent (LNREC), CO2 emissions per capita in kg (LNCO2PC), per capita GDP in constant 2010 US $ (LNRGDPC) used as the proxy of economic growth, economic globalization (LNEGI), social globalization (LNSGI), political globalization (LNPGI), and overall globalization (LNOGI) developed by Dreher, (2006), reconstructed economic globalization (LNRC\_EGI) generated by Gozgor, (2018). First, we use the classical globalization index (economic, social, political and overall globalization) of Dreher (2006). Second, we use the reconstructed economic globalization index of Gozgor (2018) that recalculates the economic globalization index by using the real trade openness instead of the nominal trade openness that enhances the economic globalization index of Dreher (2006) by using new variables, such as the trade partner diversification, international debt, and international reserves. We also use the revisited economic globalization index developed by Gygli et *al.,* (2019) that enriches the economic globalization index of Dreher (2006) by adding new variables, such as the trade partner diversification, foreign debt, international reserves, etc. Moreover, all data are taken from both World development indicators (WDI, World Bank) and Balance of Payment (BP, International Monetary Fund) and KOF index of globalization (KOF, 2018). Taking the above discussions into account, this study examines an empirical model that is consistent with the broad literature related to the impact of relevant control variables on renewable energy consumption. The control variables used in this study such as CO2 emissions, economic growth and real oil prices are based on Cheng et *al.,* (2018; 2019); Gozgor (2018); Sarkodie and Adams (2018).

***4.2. Econometric Methodology***

In this paper, we use the quantiles via moments regression analysis which was presented by the Machado and Silva Panel Quantile regression (2018). The study considers the situations under which it is desirable to estimate the regression quantiles by estimating the conditional means.

The conventional regression analysis (also known as mean regression) primarily examines the influence of explanatory variables on the conditional mean of the explained variables. Therefore, the mean regression simply underscores the central tendency of the conditional distribution, which overlooks the effect of explanatory variables for the whole distribution of the variables. Additionally, outliers are easily affected by the conventional regression. Therefore, in contrast to the mean regression, the current paper focuses on the quantile regression analysis to recognise different stages of the variables. Furthermore, the quantile regression not only considers the influence of outliers but also reduces the possible unobserved heterogeneity and covariates, which adds to relatively robust results. Moreover, it is also common that empirical studies adopt panel data to control for unrecognised heterogeneity and covariates by including the fixed effects (for e.g. quantile regression model has been Harding et al., 2020; Wang et al., 2019; and Salman et al., 2019).

We have adopted the methodology of the Machado and Silva Panel Quantile regression (2018) which focuses on the conditional location-scale model and is also widely measured by Koenker and Bassett (1982), Gutenbrunner and Jureckova (1992), Koenker and Zhao (1994), He (1997), and Zhao (2000). Moreover, the methodology suggests an estimator of the conditional quantiles accessed by merging the estimates of the location and scale functions, both of these estimates defined by conditional expectations of suitably defined variables.

The main advantage of this method is that it authorizes the use of methodologies that are specifically effective in the estimation of conditional means, for instance, differencing out individual effects in panel data models, in the same time giving information on how the regressors influence the whole conditional distribution. The informational advantages are the most interesting component of quantile regression (for e.g. the influential papers by Chamberlain, 1994, and Buchinsky, 1994). Moreover, our model approach mainly estimates of the regression quantiles that do not cross, an essential requisite usually overlooked in empirical studies (for e.g. He, 1997, and Chernozhukov et *al.,* 2010).

Moreover, it is important to note that our estimators in the model need firmer assumptions on the presence of moments than those required for the validity of the Koenker and Bassettís (1978) estimator. On the other side, our estimators analyse the same conditional quantiles under the normal asymmetric loss function, and these estimators are fundamentally robust.

The structure of the model is restrictive and estimate that covariates only affect the distribution of interest through known location and scale functions. On the other hand, researchers are usually planned to develop even robust estimations, however, in our approach the mode has the potential to test the assumption that the covariance only affects the location and scale functions, and consequently it is essential to measure whether or not our approach is robust in a specific function.

The suggested methodology is not intended to be a replacement of existing well-established estimation approaches constructed on the check function[[11]](#footnote-12). Rather, our suggested method can be considered as a supplement tool that can enhance those practices and allow the estimation of the regression quantiles in a more generalised way. For instance, the advantage of this approach when using panel data to estimate regression quantiles is that it includes individual effects. Moreover, the drawback of the quantile regressions with individual effects faced supplementary parameters (for instance, Neyman and Scott, 1948, and Lancaster, 2000) and the more recent literature present the challenges faced by the models (for e.g., Koenker, 2004, Lamarche, 2010, Canay, 2011, Galvo, 2011, Kato, Galvo and Montes-Rojas, 2012, Galvo and Wang, 2015, Galvo and Kato, 2016, and Powell, 2017). However, these approaches did not obtain any exceptional prominent acceptance because of their difficulty in computation or depending on very restrictive assumptions for the fixed effects impact on the quantile regression. Although, based on the restrictive assumption, this methodology has the benefit of having easy implementation for complex and large problems and also has the benefit of showing how the individual effects affect the whole distribution, instead of just location shifters (for e.g. Koenker (2004), Lamarche (2010), and Canay (2011). Moreover, the methodology can be used in the estimations of cross-sectional models with endogenous variables (Abadie, *et al.,* 2002; and in Chernozhukov and Hansen 2005, 2006, 2008).

In our paper renewable energy consumption is examine as alternative for oil. The increasing oil prices in recent past stimulated households and industries to reduce consumption, obtaining more efficient products and shift to renewable energy resources (EconomicReport of the President, 2006, page 243). In another study of Majum-dar and Parikh (1996) adopt oil prices and population to examine their model for demand of energy in India. Silk and Joust (1997) examine oil prices with residential energy demand in the United States. Based on publically traded companies on alternative energy, Henriques and Sadorsky (2008) identify that the stock prices of alternative energy companies react sharply to a technology stock prices than shocks to oil prices.

The major mechanism behind the economic growth and prosperity is based on energy in different forms (for e.g. residential use, transportation, power generation and industries). Moreover, advancement in growth of countries depend on the increasing demand of energy as well. The association between renewable energy demand and economic growth has been examined in different studies in literature (see for e.g. Chenet al., 2007; Lee, 2005; Narayan et al., 2007; Squalli, 2007).

Due to the recent concern of global warming, CO2 emission becomes energy policy. Any serious effort to treat with global warming is to reduce dependence on fossil fuels. Subsequently, escalation in carbon dioxide emissions, joined with increased concern over global warming, are possibly enhance consumption of renewable energy (Sadorsky, 2009).

***4.3 Model Estimation***

The basic idea of the paper is to examine the estimation of the conditional quantiles of the random variable Y’s dependence on the distributional conditional K-vector of covariates X that relate to the location-scale family.

(1)

where are unknown parameters; Z is a k-vector of known differentiable (with probability 1) transformations of the components of X with elements given by

is a called function such that where U is an unrecognised random variable, independent of X, with a density function (.) bounded away from 0 and normalized to prove the moment conditions

(2)

Equation (1) is known as the linear heteroscedasticity model where (.) is a unique function and Z=X. The model has been widely used in the literature (e.g. Koenker and Basset, 1982; Gutenbrunner and Jurecková, 1992; Koenker and Zhao, 1994; He, 1997; and Zhao, 2000).

Further, adopting Equation (2) and given the exogeneity of the regressors, the vector parameters examined under this study can be identified from the following form of moment conditions (for analysis purpose is considered an assumption)

(MC1)

where

The location-scale model determines the scale function (.), we can examine that information and develop the identification on the substitute set of moment conditions.

(MC2)

where

These settings structure the grounding of the estimation method called the Method of Moments Quantile Regression – MM-QR). The equation (MC1) indicates similarity to the Restricted Quantile Regression of He (1997) and Zhao (2000) but the suggested model examines distinctive moment conditions. Moreover, this model is very effective which makes it very simple to adopt quantile regression in a broader range of models. Especially, the MC1 is used for estimation of panel data models with fixed effects and MC2 has the benefit of examining the structural quantile functions described by Chernozhukov and Hansen (2006, 2008).

**5. Findings and Discussion**

Figure 1 displays the Q-Q plots for all the variables under the study. Basically, a Q-Q plot or a quantile-quantile plot is a graphical interpretation to explain the distributions of the data relative to a theoretical distribution such as the normal distribution (Wiley et al., 2019). Moreover, the Q-Q plot appears as a scatterplot constructed by plotting two groups of quantiles against one another. For instance, both groups of quantiles (theoretical quantile and sample quantile) representing the same distribution, we should observe that the points create a line that is approximately straight. From the following figure, we observe that all our variables are roughly plotted on the straight theoretical line. Moreover, the deviations from the straight line are minimal and this is a fair indication of normal distribution.

----------- Insert Figure1 here-----------

In Table 1, we examine the descriptive statistics. Evidently, the distribution of all the variables are moderately skewed except LNOGI, LNEGI, LNSGI and LNPGI which are highly negatively skewed. Positive excess kurtosis values indicate that the distribution has fatter tails. Correlation analysis indicates the levels of two or more variables fluctuate together. In our analysis, LNEGI has a strong positive correlation with LNOGI while LNRC\_EGI has a strong positive correlation with LNEGI.

----------- Insert Table 1 here-----------

Before analysing the panel quantile regression models, we have examined four panel unit root and stationarity tests for all variables. We have conducted three panel unit root tests including the LLC test, the IPS test and Breitung t-stat test, as well as the Hadri Z-stat stationarity test. Table 2 gives the results of those panel unit root and stationarity tests. The results demonstrate that the null hypothesis of the presence of unit root could not be rejected for all of the variables in the selected levels. However, the unit root hypothesis for all variables based on the first difference is completely rejected at the 1% level of significance. Therefore, the first difference sequence is important in our empirical analysis as well (for e.g. see [Frankel and Rose, 1996](https://www.sciencedirect.com/science/article/pii/S0261560600000486#BIB11); [Oh, 1996](https://www.sciencedirect.com/science/article/pii/S0261560600000486" \l "BIB25); [Lothian, 1997](https://www.sciencedirect.com/science/article/pii/S0261560600000486" \l "BIB21); and [Taylor, 1996](https://www.sciencedirect.com/science/article/pii/S0261560600000486" \l "BIB31)). Moreover, our results are robust to cross-sectional dependence.

----------- Insert Table 2 here-----------

The foregoing discussion implies that we should adopt an effective and useful statistical inference, especially when the underlying assumptions are violated since depending on a robust standard error is usually common. On the basis of the evidence currently available, it seems fair to suggest that most commonly well-known covariance matrix estimators are developed by Eicker (1967), Huber (1967) and White (1980). Further research in this area may include Arellano (1987), Froot (1989) and Rogers (1993) which specify that it is adept to some extent to ease the assumption of independently distributed residuals. Moreover, their generalised estimator specifies consistent standard errors on condition that the residuals are correlated within but uncorrelated between clusters.

Newey and West (1987) developed another useful method to find heteroscedasticity and autocorrelation established on some lag consistent standard errors. They have included GMM as well as the addition of White’s estimator and is known as the Newey-West estimator with a consideration of zero lag length, similar to the White estimator.

Driscoll and Kraay (1998) introduced a non-parametric covariance matrix estimator which gives heteroscedasticity and autocorrelation consistent standard errors. Moreover, it specifies a robust to spatial and temporal dependence.

From Tables 3 to 8, we investigate alternative fixed effect models. We have analysed the OLS, White, Rogers, Newey-West, Driscoll-Kraay tests and OLS MOM models. From Tables 3 to 8, we have examined the association between renewable energy consumption and the control variables such as globalization, real GDP, oil prices and carbon emissions. We place major emphasis on the effect of nuanced globalization on renewable energy as the level of globalization is examined through three distinct indexes of globalization such as “classic”, “reconstructed” and “revisited” (for e.g. see Dreher, 2006; Gozgor, 2018; and Gygli et *al.,* 2019). Likewise, a higher level of globalization also includes (overall, economic, social and political) factors which effect the renewable energy consumption during the reconstructed and revisited economic globalization.

In Table 3of Model 1, the results of the Driscoll-Kraay test has a stronger and positive significant impact on total renewable energy consumption as a per cent of GDP (LNREC), in comparison to other fixed effect models. In the other words, real capita income to GDP (LNRGPDC), real oil prices (LNROP), CO2 emissions per capita in kg (LNCO2PC) and overall globalization (LNOGI) have a positive and significant effect on the total renewable energy consumption (for e.g. see Vasylieva et al., 2019; Pickl, 2019 and Zhao et al., 2018).

----------- Insert Table 3 here-----------

In Table 4 of Model 2, we have included economic globalization in place of overall globalization along with other common variables. The results of the estimated White fixed effect and Rogers fixed effects have a strong and positively significant influence on total renewable consumption. Such as real capita income to GDP (LNRGPDC), real oil prices (LNROP), and Economic Globalization (LNEGI) has a positive and significant effect on the total renewable energy consumption under the model assumptions of White FE and Rogers FE. However, the CO2 emissions per capita in kg (LN CO2PC) are positive but they show an insignificant influence on total renewable energy consumption and the results are bring into line with study of (Lin and Moubarak, 2014).

----------- Insert Table 4 here-----------

By considering Table 5 of Model 3, this model includes social globalization (LNSGI) along with the earlier three common variables: real capita income to GDP (LNRGPDC), real oil prices (LNROP) and CO2 emissions per capita in kg (LNCO2PC). The results indicate that the OLS, White and Rogers models yield a strong and positive significant impact of real capita income to GDP (LNRGPDC), real oil prices (LNROP), and social globalization (LNSGI) on total renewable energy consumption (LNREC), in comparison with other models and endorse with the studies of (Marques et al., 2017). However, the CO2 emissions per capita in kg (LNCO2PC) results are similar to those in Model 2, since they indicate a positive but insignificant influence on total renewable energy consumption.

----------- Insert Table 5 here-----------

In Table 6 of Model 4, we have considered Political Globalization (LNPGI) in addition to real capita income to GDP (LNRGPDC), real oil prices (LNROP), CO2 emissions in kg per capita (LNCO2PC). The results demonstrate a strong and significantly positive association of the real capita income to GDP (LNRGPDC), real oil prices (LNROP), and Political Globalization (LNPGI) with total renewable energy consumption (LNREC) in the following fixed effects models OLS, White, Rogers and Driscoll-Kraay and evidence of related research also examine by (Destek, 2019). Although, CO2 emissions in kg per capita (LN CO2PC) indicating positive but insignificant influence towards total renewable energy consumption.

----------- Insert Table 6 here-----------

In Table 7 of Model 5, we have measured economic globalization by the reconstructed globalization index (LNRC\_EGI). Along with the inclusion of the common globalization variables such as real capita income to GDP (LNRGPDC), real oil prices (LNROP), CO2 emissions per capita in kg (LN CO2PC), the results indicate that the White and the Rogers have a positive and significant influence of the real capita income on GDP (LNRGPDC) and the real oil prices (LNROP) towards total renewable energy consumption. Moreover, a negative and significant influence of the reconstructed economic globalization index (LNRC\_EGI) is observed on total renewable energy consumption (LNREC) as well. The negative influence of reconstructed economic globalization index enhanced the carbon emissions and negatively effects on renewable energy (for e.g. see Destek, 2019; Kalayci, 2019 and Khan et al., 2019). On the other hand, CO2 emissions per capita in kg (LN CO2PC) have an insignificant influence on total renewable energy consumption in all fixed effects models.

----------- Insert Table 7 here-----------

In Table 8 of Model 6, we have adopted a variable for economic globalization by measuring it through the revisited economic globalization index (LNREVEGI), in addition to including the other common globalization variables such as real capita income to GDP (LNRGPDC), real oil prices (LNROP), CO2 emissions per capita in kg (LN CO2PC). The outcome has a resemblance with that of Model 5 in the sense that White and Rogers have a strong positive and significant effect on the real GDP per capita (LNRGPDC) and real oil prices (LNROP) but have a negative and significant influence for the revisited economic globalization index (LNREVEGI) on total renewable energy consumption (LNREC), therefore our results are bring into line with (for e.g. see Destek, 2019; Kalayci, 2019 and Khan et al., 2019). On the other hand, CO2 emissions per capita in kg (LNCO2PC) has an insignificant influence towards total renewable energy consumption in the fixed effect models except the OLSMO.

----------- Insert Table 8 here-----------

The following analyses presented in Tables 9 to 14 are based on the quantiles via the moments regression analysis presented by Machado and Silva Panel Quantile regression (2018). The quantile regression estimates provide one solution to each quantile. By using this methodology, we can determine the total renewable energy consumption throughout the conditional distribution, specifically in the OECD countries with consideration of the most and the least renewable energy consumption. Moreover, the other advantage of this methodology is that it helps one understand what happens at the extremes of the distribution. In addition, the panel quantile regression outcomes are robust and help in the interpretation of the results of the variables. They are also more adequate than those of the OLS regression.

In Table 9, we have used similar explanatory variables as in Table 3 in our panel quantile regression. We have noticed that real capita income to GDP (LNRGPDC), real oil prices (LNROP) and overall globalization (LNOGI) are clearly significant and positive at the lower and higher quantiles. This finding indicates that total renewable energy consumption strongly relying on real capita income to GDP (LNRGPDC), real oil prices (LNROP) and overall globalization (LNOGI) in the OECD countries under consideration (for e.g. see Vasylieva et al., 2019; Pickl, 2019 and Zhao et al., 2018). On the other hand, coefficient of CO2 emissions per capita in kg (LN CO2PC) is negatively significant at the lower quantile (5th);, but at the (10th to 80th) quantiles, it becomes insignificant and then turns positively significant at the higher quantiles. This finding implies that a higher renewable energy consumption leads to lower carbon emissions in the higher renewable energy consumption countries, whereas the opposite holds true in the lower-renewable energy consumption countries, our results are align with arguments of (Nguyen and Kakinaka, 2019).

----------- Insert Table 9 here-----------

In Table 10 of Model 2, we have used the same common globalization variables, i.e. real capita income to GDP (LNRGPDC), real oil prices (LNROP), CO2 emissions per capita in kg (LNCO2PC) and also included the additional variable called economic globalization (LNEGI). The results for the common globalization variables are similar to those in Table 9 of Model 1 (for e.g. see Vasylieva et al., 2019; Pickl, 2019 and Zhao et al., 2018). However, economic globalization is negative and significant at the higher quantiles (i.e., 90th) but significantly positive at the 2nd to 7th quantiles. These results imply that economic globalization increases renewable energy consumption in the middle quantile level by enabling the importation of advanced technology. However, in the lower and higher quantiles, economic globalization increases non-renewable (coal, wood) energy consumption because the livelihood strategy follows in the lower quantiles and speedy growth strategy follows in the higher quantiles (for e.g. see Sasana and Aminata 2019).

----------- Insert Table 10 here-----------

In Table 11 of Model 3, along with our common globalization variables i.e. real capita income to GDP (LNRGPDC), real oil prices (LNROP), CO2 emissions per capita in kg (LN CO2PC), we have included social globalization (LNSGI). The results indicate that social globalization has a positively significant impact at the lower to middle quantiles (10% to 50%) and then becomes positively insignificant. However, at the higher quantile (95%) it turns again to be significantly positive. It indicates that social globalization factors have strong influence on the total renewable consumptions as social norms of globalization increases the dependency on the renewable energy consumption in OECD countries, our results can be relate with study of (Marques et al., 2017). Moreover, the common globalization variables illustrate similar results as demonstrated earlier in Table 9 (for e.g. see Vasylieva et al., 2019; Pickl, 2019 and Zhao et al., 2018).

----------- Insert Table 11 here-----------

In Table 12 of Model 4, we have included the political globalization (LNPGI) along, with three common globalization variables i.e. real capita income to GDP (LNRGPDC), real oil prices (LNROP), CO2 emissions per capita in kg (LNCO2PC), using quantile via moments regression analysis as presented in the Machado and Silva Panel Quantile regression (2018). The outcome indicates that political globalization is strongly and positively significant in the lowest to highest quantiles (5% to 95%). It clearly indicates that political globalization promotes strongly total renewable energy consumption in 30 OECD countries over the period 1970 to 2015. Recently OECD countries emphasize on renewable energy programs and politicians have shown interest and shifting their reliance on renewable energy (Nicolli and Vona, 2019). The other explanatory variables present similar results as mentioned earlier in Table 9 (for e.g. see Vasylieva et al., 2019; Pickl, 2019 and Zhao et al., 2018).

----------- Insert Table 12 here-----------

In Table 13 of Model 5, we incorporate the reconstructed economic globalization (RC\_EGI) along with the common globalization variables i.e. real capita income to GDP (LNRGPDC), real oil prices (LNROP), CO2 emissions in kg per capita (LNCO2PC). The results indicate that the reconstructed economic globalization is negatively significant at the lower quantiles (5%, 10% and 40%), however, it is actively negatively significant at higher quantiles i.e. (i.e., 80%, 90% and 95%). It demonstrates that the reconstructed economic globalization reduces the influence of renewable energy consumption on OECD countries (for e.g. see Destek, 2019; Kalayci, 2019 and Khan et al., 2019). The other explanatory variables illustrate similar results as demonstrated earlier in Table 9 (for e.g. see Vasylieva et al., 2019; Pickl, 2019 and Zhao et al., 2018).

----------- Insert Table 13 here-----------

In Table 14 of Model 6, we replace the old measure of globalization by the revisited economic globalization (REVEGI) variable and present the results measuring the effect on total renewable energy consumption. The revisited economic globalization has a resemblance with the results of the reconstructed economic globalization. The lower quantiles (5% and 10%) have, respectively, negatively significant and strongly negatively significant at higher quantiles (i.e., 70%, 80%, 90% and 95%). Similarly, the impact of the revisited economic globalization reduces the effect of renewable energy consumption on OECD countries (for e.g. see Destek, 2019; Kalayci, 2019 and Khan et al., 2019). Moreover, the common globalization variables show similar results as indicated earlier in Table 9 (for e.g. see Vasylieva et al., 2019; Pickl, 2019 and Zhao et al., 2018).

----------- Insert Table 14 here-----------

**6. Conclusions and Policy Implications**

The main aim of this study is to examine the impact of real capita income or GDP, real oil price, CO2 emissions and the control variables of globalization on total renewable energy consumption, using panel data for 30 OECD countries over the period 1970-2015. We use the control variables such as per capita income, the real oil price, and the level of carbon dioxide emissions in the relationship between the pattern of globalization(s) and its impact on renewable energy consumption to obtain the robust empirical findings. We use real gross domestic product (GDP) because as income increases energy consumption also increases, it shows that GDP also considers as a factor may impact on renewable energy consumption. The oil prices affect the renewable energy via fossil fuels. Moreover, the carbon emissions also use a factor effecting renewable energy consumption (Omri and Nguyen, 2014). We use these set of control variables as per the literature based on Cheng et *al.,* (2018; 2019); Gozgor (2018); Sarkodie and Adams (2018). The main contribution of the paper based on the different configuration of globalization of Konjunkturforschungsstelle (KOF; 2018). Our paper use classic globalisation, reconstructed economic globalisation and revisited economic globalisation and its influence on renewable energy consumption. Moreover, we have applied novel technique of Machado and Silva Panel quantile regression (2018) to examine the impact of globalisation and renewable energy consumption to achieve robust results for energy globalization nexus. Moreover, our methodology of quantile regression provides more explicit results than ordinary least square method because it is taking in account the heterogeneity and distributional heterogeneity that are neglected by ordinary least square method. Further the method is explaining the entire conditional distribution of dependent variable and also providing robust outlying observation of the exogenous variable. The empirical results demonstrate the existence of a long-run relationship between the renewable energy consumption and the control variables. Specifically, the results show a significantly positive relationship between per capita income, real price of oil and carbon emissions per capita and renewable energy.

Higher levels of globalization (overall, economics, social and political) widely stimulate renewable energy consumption. On the hand, the results show that the reconstructed and revisited economic globalization reduces renewable energy consumption, and this conclusion is also robust to different measures of economic globalization. They also confirm that renewable energy consumption boosts the domestic economy in the middle section by importing modern and advanced technology. However, the lower and higher sections rely more on non-renewable (coal, wood) energy as a result of the livelihood approach that depends on wood and coal (lower quantiles section) to generate energy and of the accelerated growth (higher quantiles section), respectively, which deteriorates the quality of the environment without caring about the essence of globalization.

Based on the results of the study, the following policy implications should be adopted to help improve environmental quality in OECD countries. First, the host countries should measure the per capita income before assessing the introduction of total renewable energy consumption into the country. Second, each OECD country should consume energy efficiently and establish energy development programs to educate citizens how to shift from fossil fuels (such as oil and coal), towards more green renewable energy system. Moreover, governments should provide subsidies to encounter the usage of renewable energy consumption and educate consumers of starting from the grass root level of the benefits of renewable energy consumption (such as reducing air pollution, decreasing dependence on coal and other fossil fuels), and welcoming industries’ initiatives related to renewable energy resources. Third, the findings suggest that higher carbon emissions countries could take advantage of higher economic growth and ultimately increase the population as well. Therefore, higher-emission countries in OECD should not only address economic growth but should also pay attention to the growing population to reduce carbon emissions. In addition, OECD countries should also enhance globalization through more trade openness which increases the reliance on renewable energy consumption. Finally, the most important implication of our findings is that the design of uniform renewable energy consumption policies equally across OECD countries are likely to lead to different levels of renewable energy consumption requirements. Therefore, renewable energy consumption parameters should be measured and developed differently across OECD countries.

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**References**

Abadie, A., Angrist, J. and Imbens, G. (2002). Instrumental variables estimates of the effect of subsidized training on the quantiles of trainee earnings. *Econometrica*, 70(1), 91-117.

Aguirre, M., and Ibikunle, G.(2014). Determinants of renewable energy growth: A global sample analysis*. Energy Policy*, 69, 374–384.

Aissa, M.S.B., Jebli, M.B., and Youssef, S.B. (2014). Output, renewable energy consumption and trade in Africa. *Energy Policy*, 66, 11–18.

Akram, R., Chen, F., Khalid, F., Ye, Z., and Majeed, M. T. (2020). Heterogeneous effects of energy efficiency and renewable energy on carbon emissions: Evidence from developing countries. *Journal of Cleaner Production*, *247*, 119122.

Alam, M. M., and Murad, M. W. (2020). The impacts of economic growth, trade openness and technological progress on renewable energy use in organization for economic co-operation and development countries. *Renewable Energy*, *145*, 382-390.

Alper, A., and Oguz, O. (2016). The role of renewable energy consumption in economic growth: Evidence from asymmetric causality. *Renewable and Sustainable Energy Reviews,* 60, 953–959.

Ang, J. B. (2007). CO2 emissions, energy consumption, and output in France. *Energy Policy*, *35*(10), 4772-4778.

Ang, J. B. (2008). Economic development, pollutant emissions and energy consumption in Malaysia. *Journal of Policy Modeling*, *30*(2), 271-278.

Apergis, N., and Payne, J.E. (2010a). Renewable energy consumption and growth in Eurasia. *Energy Economics*, 32 (6), 1392–1397.

Apergis, N., and Payne, J.E. (2010b). Renewable energy consumption and economic growth: Evidence from a panel of OECD countries. *Energy Policy*, 38 (1), 656–660.

Apergis, N., and Payne, J. E. (2015). Renewable energy, output, carbon dioxide emissions, and oil prices: evidence from South America. *Energy Sources, Part B: Economics, Planning, and Policy*, *10*(3), 281-287.

Arellano, M. (1987). Practitioners’ corner: Computing Robust Standard Errors for Within‐groups Estimators. *Oxford bulletin of Economics and Statistics*, 49(4), 431-434.

Asafu-Adjaye, J. (2000). The relationship between energy consumption, energy prices and economic growth: time series evidence from Asian developing countries. *Energy Economics*, *22*(6), 615-625.

Baek, J., Cho, Y., and Koo, W.W. (2009). The environmental consequences of globalization: A country-specific time-series analysis. *Ecological Economics*, 68 (8–9), 2255–2264.

Belaid, F., and Zrelli, M. H. (2019). Renewable and non-renewable electricity consumption, environmental degradation and economic development: Evidence from Mediterranean countries. *Energy Policy*, *133*, 110929.

Bhattacharya, B., Paramati, S.R., Ozturk, I., and Bhattacharya, S. (2016). The effect of renewable energy consumption on economic growth: Evidence from top 38 countries. *Applied Energy*, 162, 733–741.

Breitung, J. (2000). “The local power of some unit root tests for panel data”. In B.H. Baltagi (Eds.), *Advances in Econometrics, Volume 15: Nonstationary Panels, Panel Cointegration, and Dynamic Panels*, (161–178), Amsterdam: JAY Press.

Broadstock, D. C., Cao, H., and Zhang, D. (2012). Oil shocks and their impact on energy related stocks in China. *Energy Economics*, *34*(6), 1888-1895.

Bu, M., Lin, C.T., and Zhang, B. (2016). Globalization and climate change: new empirical panel data evidence. *Journal of Economic Surveys*, 30 (3), 577–595.

Buchinsky, M. (1994). Changes in the US wage structure 1963-1987: Application of quantile regression. Econometrica: *Journal of the Econometric Society*, 405-458.

Canay, I.A. (2011). A simple approach to quantile regression for panel data. *The Econometrics Journal*, 14(3), 368-386.

Chamberlain, G. (1994). Quantile regression, censoring, and the structure of wages. *In Advances in Econometrics: Sixth World Congress* (Vol. 2, 171-209).

Chen, Y. (2018). Factors influencing renewable energy consumption in China: An empirical analysis based on provincial panel data. *Journal of Cleaner Production*, 174, 605–615.

Chen, C., Pinar, M., and Stengos, T. (2020). Renewable energy consumption and economic growth nexus: Evidence from a threshold model. *Energy Policy*, *139*, 111295.

Cheng, C., Ren, X., Wang, Z., and Yan, C. (2019). Heterogeneous impacts of renewable energy and environmental patents on CO2 emission-Evidence from the BRIICS. *Science of the Total Environment*, *668*, 1328-1338.

Cheng, C., Ren, X., Wang, Z., and Shi, Y. (2018). The impacts of non-fossil energy, economic growth, energy consumption, and oil price on carbon intensity: evidence from a panel quantile regression analysis of EU 28. *Sustainability*, *10*(11), 4067.

Cheng, Y., Zhang, N., Kirschen, D. S., Huang, W., and Kang, C. (2020). Planning multiple energy systems for low-carbon districts with high penetration of renewable energy: An empirical study in China. *Applied Energy*, *261*, 114390.

Cheon, A., and Urpelainen, J. (2012). Oil prices and energy technology innovation: An empirical analysis. *Global Environmental Change*, *22*(2), 407-417.

Chernozhukov, V., Fernández Val, I. and Galichon, A. (2010). Quantile and probability curves without crossing. *Econometrica*, 78(3), 1093-1125.

Chernozhukov, V. and Hansen, C. (2005). An IV model of quantile treatment effects. *Econometrica*, 73(1), 245-261.

Chernozhukov, V. and Hansen, C. (2006). Instrumental quantile regression inference for structural and treatment effect models. *Journal of Econometrics*, 132(2), 491-525.

Chernozhukov, V. and Hansen, C. (2008). Instrumental variable quantile regression: A robust inference approach. *Journal of Econometrics*, 142(1), 379-398.

Copeland, B.R. (2005). Policy endogeneity and the effects of trade on the environment. *Agricultural and Resource Economics Review*, 34(1), 1–15.

Copeland, B.R., and Taylor, M.S. (1994). North-South trade and the environment. *The Quarterly Journal of Economics*, 109 (3), 755–787.

Copeland, B.R., and Taylor, M.S. (2004). Trade, growth, and the environment. *Journal of Economic Literature,* 42 (1), 7–71.

Damette, O., and Delacote, P. (2012). On the economic factors of deforestation: What can we learn from quantile analysis?. *Economic Modelling*, *29*(6), 2427-2434.

Dedeoğlu, D., and Kaya, H. (2013). Energy use, exports, imports and GDP: New evidence from the OECD countries. *Energy Policy*, 57, 469–476.

Destek, M.A., 2019. Investigation on the role of economic, social, and political globalization on environment: evidence from CEECs. *Environmental Science and Pollution Research*, pp.1-14.

Destek, M. A., and Sinha, A. (2020). Renewable, non-renewable energy consumption, economic growth, trade openness and ecological footprint: Evidence from organisation for economic Co-operation and development countries. *Journal of Cleaner Production*, *242*, 118537.

Destek, M. A., and Aslan, A. (2020). Disaggregated renewable energy consumption and environmental pollution nexus in G-7 countries. *Renewable Energy*, *151*, 1298-1306.

Dong, K., Sun, R., Jiang, H., & Zeng, X. (2018a). CO2 emissions, economic growth, and the environmental Kuznets curve in China: What roles can nuclear energy and renewable energy play?. *Journal of Cleaner Production*, *196*, 51-63.

Dong, K., Sun, R., & Dong, X. (2018b). CO2 emissions, natural gas and renewables, economic growth: assessing the evidence from China. *Science of the Total Environment*, *640*, 293-302.

Dreher, A. (2006). Does globalization affect growth? Evidence from a new index of globalization. *Applied Economics*, 38 (10), 1091–1110.

Driscoll, J.C. and Kraay, A.C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. Review of Economics and Statistics, 80(4),.549-560.

Eicker, F. (1967). Limit theorems for regressions with unequal and dependent errors. *In Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability* 1(1),. 59-82.

Eskeland, G.S., and Harrison, A.E. (2003). Moving to greener pastures? Multinationals and the pollution haven hypothesis. *Journal of Development Economics*, 70 (1), 1–23.

Fan, W., and Hao, Y. (2020). An empirical research on the relationship amongst renewable energy consumption, economic growth and foreign direct investment in China. *Renewable Energy*, *146*, 598-609.

Flores, C. A., Flores-Lagunes, A., and Kapetanakis, D. (2014). Lessons from quantile panel estimation of the environmental Kuznets curve. *Econometric Reviews*, *33*(8), 815-853.

Froot, K.A. (1989). Consistent covariance matrix estimation with cross-sectional dependence and heteroskedasticity in financial data. *Journal of Financial and Quantitative Analysis*, 24(3), 333-355.

Galvao Jr, A.F. (2011). Quantile regression for dynamic panel data with fixed effects. *Journal of Econometrics*, 164(1), 142-157.

Galvao, A.F. and Kato, K. (2016). Smoothed quantile regression for panel data. *Journal of Econometrics*, 193(1), .92-112.

Galvao, A.F. and Wang, L. (2015). Efficient minimum distance estimator for quantile regression fixed effects panel data. *Journal of Multivariate Analysis*, 133,.1-26.

Geller, H., Harrington, P., Rosenfeld, A. H., Tanishima, S., and Unander, F. (2006). Polices for increasing energy efficiency: Thirty years of experience in OECD countries. *Energy Policy*, *34*(5), 556-573.

Ghali, K. H., and El-Sakka, M. I. (2004). Energy use and output growth in Canada: a multivariate cointegration analysis.*Energy Economics*, *26*(2), 225-238.

Gourevitch, P. (1978). The second image reversed: the international sources of domestic politics. *International Organization*, *32*(4), 881-912.

Gozgor, G., Mahalik, M. K., Demir, E., and Padhan, H. (2020). The impact of economic globalization on renewable energy in the OECD countries. *Energy Policy*, *139*, 111365.

Gozgor, G. (2018). Robustness of the KOF index of economic globalisation. *The World Economy*, 41 (2), 414–430.

Gozgor, G., and Ranjan, P. (2017). Globalisation, inequality and redistribution: Theory and evidence. *The World Economy*, 40 (12), 2704–2751.

Gozgor, G. (2018). A new approach to the renewable energy-growth nexus: evidence from the USA. *Environmental Science and Pollution Research*, *25*(17), 16590-16600.

Gutenbrunner, C. and Jurecková, J. (1992). Regression rank scores and regression quantiles. *The Annals of Statistics*, 305-330.

Gygli, S., Haelg, F., and Sturm, J–E. (2018). The KOF Globalisation Index – Revisited. *KOF Working Papers*, No. 439.

Hadri, K. (2000). Testing for stationarity in heterogeneous panel data. *Econometrics Journal*, 3 (2), 148–161.

Harding, M., Lamarche, C. and Pesaran, M.H., 2020. Common correlated effects estimation of heterogeneous dynamic panel quantile regression models. *Journal of Applied Econometrics*, 35(3), pp.294-314.

He, X. (1997). Quantile curves without crossing. *The American Statistician*, 51(2), 186-192.

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

Hsiao, C. Y. L., Lin, W., Wei, X., Yan, G., Li, S., and Sheng, N. (2019). The Impact of International Oil Prices on the Stock Price Fluctuations of China’s Renewable Energy Enterprises. *Energies*, *12*(24), 4630.

Huber, P.J. (1967). The behaviour of maximum likelihood estimates under nonstandard conditions. *In Proceedings of the fifth Berkeley Symposium on Mathematical Statistics and Probability* 1(1), 221-233.

Ikenberry, G. J. (1986). The irony of state strength: comparative responses to the oil shocks in the 1970s. *International Organization*, *40*(1), 105-137.

Im, K.S., Pesaran, M.H., and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115 (1), 53–74.

Inchauspe, J., Ripple, R. D., and Trück, S. (2015). The dynamics of returns on renewable energy companies: A state-space approach. *Energy Economics*, *48*, 325-335.

Jacqmin, J. (2018). The role of market-oriented institutions in the deployment of renewable energies: Evidences from Europe. *Applied Economics*, 50(2), 202–215.

Kalayci, C., 2019. The impact of economic globalization on CO2 emissions: the case of NAFTA countries. *International Journal of Energy Economics and Policy*, 9(1), p.356.

Kao, C.D. (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics*, 90 (1), 1–44.

Kato, K., Galvao Jr, A.F. and Montes-Rojas, G.V. (2012). Asymptotics for panel quantile regression models with individual effects. *Journal of Econometrics*, 170(1), 76-91.

Khan, M.K., Teng, J.Z., Khan, M.I. and Khan, M.O., 2019. Impact of globalization, economic factors and energy consumption on CO2 emissions in Pakistan. *Science of the total environment*, 688, pp.424-436.

Koenker, R. (2004). Quantile regression for longitudinal data. *Journal of Multivariate Analysis*, 91(1), pp.74-89.

Koenker, R. and Bassett Jr, G. (1978). Regression quantiles. Econometrica: *Journal of the Econometric Society*, 33-50

Koenker, R. and Bassett Jr, G. (1982). Robust tests for heteroscedasticity based on regression quantiles. Econometrica: *Journal of the Econometric Society*, pp.43-61.

Koenker, R. and Zhao, Q. (1994). L-estimatton for linear heteroscedastic models. *Journal title of Nonparametric Statistics*, 3(3-4), 223-235.

Kutan, A. M., Paramati, S. R., Ummalla, M., and Zakari, A. (2018). Financing renewable energy projects in major emerging market economies: Evidence in the perspective of sustainable economic development. *Emerging Markets Finance and Trade*, *54*(8), 1761-1777.

Kyritsis, E., and Serletis, A. (2019). Oil prices and the renewable energy sector. *The Energy Journal*, *40*(The New Era of Energy Transition).

Lamarche, C. (2010). Robust penalized quantile regression estimation for panel data. *Journal of Econometrics*, 157(2), 396-408.

Lancaster, T. (2000). The incidental parameter problem since 1948. *Journal of Econometrics*, 95(2), 391-413.

Lean, H.H., and Smyth, R. (2010). Multivariate Granger causality between electricity generation, exports, prices and GDP in Malaysia. *Energy*, 35 (9), 3640–3648.

Lee, C. C. (2005). Energy consumption and GDP in developing countries: a cointegrated panel analysis. *Energy Economics*, *27*(3), 415-427.

Levin, A., Lin, C–F., and Chu, C–S.J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics*, 108 (1), 1–24.

Lin, B., Omoju, O.E., and Okonkwo, J.U. (2016). Factors influencing renewable electricity consumption in China. *Renewable and Sustainable Energy Reviews*, 55, 687–696.

Lin, B., and Moubarak, M. (2014). Renewable energy consumption – economic growth nexus for China. *Renewable and Sustainable Energy Reviews*, 40, 111–117.

Liu, F., Tait, S., Schellart, A., Mayfield, M., and Boxall, J. (2020). Reducing carbon emissions by integrating urban water systems and renewable energy sources at a community scale. *Renewable and Sustainable Energy Reviews*, *123*, 109767.

Machado, J.A. and Santos Silva, J.M.C. (2018). Quantiles via Moments. *Journal of Econometrics*.

Marques, A.C., Fuinhas, J.A., and Manso, J.P. (2010). Motivations driving renewable energy in European countries: A panel data approach. *Energy Policy*, 38, 6877–6885.

Marques, L.M., Fuinhas, J.A. and Marques, A.C., 2017. Augmented energy-growth nexus: economic, political and social globalization impacts. *Energy Procedia*, 136, pp.97-101.

Masih, A. M., and Masih, R. (1997). On the temporal causal relationship between energy consumption, real income, and prices: some new evidence from Asian-energy dependent NICs based on a multivariate cointegration/vector error-correction approach. *Journal of Policy Modeling*, *19*(4), 417-440.

Narayan, P.K., and Smyth, R. (2009). Multivariate Granger causality between electricity consumption, exports and GDP: Evidence from a panel of Middle Eastern countries. *Energy Policy*, 37 (1), 229–236.

Narayan, P. K., and Singh, B. (2007). The electricity consumption and GDP nexus for the Fiji Islands. *Energy Economics*, *29*(6), 1141-1150.

Newey, W.K. and West, K.D. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, 777-787.

Neyman, J. and Scott, E.L. (1948). Consistent estimates based on partially consistent observations. Econometrica: *Journal of the Econometric Society*, 1-32.

Nicolli, F. and Vona, F., 2019. Energy market liberalization and renewable energy policies in OECD countries. *Energy policy*, 128, pp.853-867.

Nilsson, M. M. (2019). The Effect of Oil Prices on Patents in Renewable Energy: A DTC Approach.

Nguyen, K.H. and Kakinaka, M., 2019. Renewable energy consumption, carbon emissions, and development stages: Some evidence from panel cointegration analysis. *Renewable Energy*, 132, pp.1049-1057.

Oh, W., and Lee, K. (2004). Energy consumption and economic growth in Korea: testing the causality relation. *Journal of Policy Modeling*, *26*(8-9), 973-981.

Omri, A., and Nguyen, D.K. (2014). On the determinants of renewable energy consumption: International evidence. *Energy*, 72, 554–560.

Ozturk, I., and Acaravci, A. (2013) .The long-run and causal analysis of energy, growth, openness and financial development on carbon emissions in Turkey.*Energy Economics*, 36, 262–267.

Paramati, S.R., Ummalla, M., and Apergis, N. (2016). The effect of foreign direct investment and stock market growth on clean energy use across a panel of emerging market economies. *Energy Economics*, 56, 29–41.

Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics*, 61 (S1), 653–670.

Pedroni, P. (2001). “Fully modified OLS for heterogeneous cointegrated panels”. In B.H. Baltagi, T.B. Fomby, and R.C. Hill (Eds.), *Nonstationary Panels, Panel Cointegration, and Dynamic Panels*, (pp. 93–130). Bingley: Emerald Group Publishing Limited.

Pickl, M.J., 2019. The renewable energy strategies of oil majors–From oil to energy? *Energy Strategy Reviews*, 26, p.100370.

Powell, D. (2016). Quantile regression with nonadditive fixed effects. *Quantile Treatment Effects*.

Rafiq, S., and Alam, K. (2010). Identifying the determinants of renewable energy consumption in leading renewable energy investor emerging countries. *39th Australian Conference of Economists, held* (pp. 27-29).

Rafiq, S., and Salim, R. A. (2009). Temporal causality between energy consumption and income in six Asian emerging countries. *Applied Economics Quarterly*, *55*(4), 335.

Rahman, S.M., and Miah, M.D. (2017). The impact of sources of energy production on globalization: Evidence from panel data analysis. *Renewable and Sustainable Energy Reviews*, 74, 110–115.

Rahman, M. M., and Velayutham, E. (2020). Renewable and non-renewable energy consumption-economic growth nexus: New evidence from South Asia. *Renewable Energy*, *147*, 399-408.

Razmi, S. F., Bajgiran, B. R., Behname, M., Salari, T. E., and Razmi, S. M. J. (2020). The relationship of renewable energy consumption to stock market development and economic growth in Iran. *Renewable Energy*, *145*, 2019-2024.

Reboredo, J. C., Rivera-Castro, M. A., and Ugolini, A. (2017). Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. *Energy Economics*, *61*, 241-252.

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

Ruhul, S., Rafiq, S., and Hassan, A. K. (2008). Causality and dynamics of energy consumption and output: Evidence from non-OECD Asian countries. *Journal of Economic Development*, *33*(2), 1-26.

Rogers, W. (1993). Regression standard errors in clustered samples. *Stata Technical Bulletin*, 13, 19-23.

Sadorsky P. (2009a). Renewable energy consumption, CO2 emissions and oil prices in the G7 countries. *Energy Economics*, 31 (3), 456–462.

Sadorsky P. (2009b). Renewable energy consumption and income in emerging economies. *Energy Policy*, 37 (10), 4021–4028.

Sadorsky, P. (2011). Trade and energy consumption in the Middle East. *Energy Economics*, 33 (5), 739–749.

Sadorsky, P. (2012a). Energy consumption, output and trade in South America. *Energy Economics*, 34(2), 476–488.

Sadorsky, P. (2012b). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy economics*, *34*(1), 248-255.

Salim R.A.,and Rafiq S. (2012). Why do some emerging economies proactively accelerate the adoption of renewable energy? *Energy Economics*, 34 (4), 1051–1057.

Salman, M., Long, X., Dauda, L., Mensah, C.N. and Muhammad, S., 2019. Different impacts of export and import on carbon emissions across 7 ASEAN countries: A panel quantile regression approach. *Science of the total environment*, 686, pp.1019-1029.

Sarkodie, S. A., and Adams, S. (2018). Renewable energy, nuclear energy, and environmental pollution: accounting for political institutional quality in South Africa. *Science of the Total Environment*, *643*, 1590-1601.

Sasana, H. and Aminata, J., 2019. Energy subsidy, energy consumption, economic growth, and carbon dioxide emission: Indonesian case studies. *International Journal of Energy Economics and Policy*, 9(2), p.117.

Sener, S.E.C., Sharp, J.L., and Anctil, A. (2018). Factors impacting diverging paths of renewable energy: A review. *Renewable and Sustainable Energy Reviews*, 81, 2335–2342.

Shah, I. H., Hiles, C., and Morley, B. (2018). How do oil prices, macroeconomic factors and policies affect the market for renewable energy?. *Applied Energy*, *215*, 87-97.

Shahbaz, M., Lahiani, A., Abosedra, S., and Hammoudeh, S. (2018b). The role of globalization in energy consumption: A quantile cointegrating regression approach. *Energy Economics*, 71, 161–170.

Shahbaz, M., Lean, H.H., and Farooq, A. (2013). Natural gas consumption and economic growth in Pakistan. *Renewable and Sustainable Energy Reviews*, 18, 87–94.

Shahbaz, M., Mallick, H., Mahalik, M.K., and Sadorsky, P. (2016). The role of globalization on the recent evolution of energy demand in India: Implications for sustainable development. *Energy Economics*, 55, 52–68.

Shahbaz, M., Nasreen, S., Ling, C.H., and Sbia, R. (2014). Causality between trade openness and energy consumption: What causes what in high, middle and low income countries? *Energy Policy*, 70, 126–143.

Shahbaz, M., Shahzad, S.J.H., Mahalik, M.K., and Sadorsky, P. (2018a). How strong is the causal relationship between globalization and energy consumption in developed economies? A country-specific time-series and panel analysis. *Applied Economics*, 50 (13), 1479–1494.

Soytas, U., and Sari, R. (2007). The relationship between energy and production: evidence from Turkish manufacturing industry. *Energy Economics*, *29*(6), 1151-1165.

Vasylieva, T., Lyulyov, O., Bilan, Y. and Streimikiene, D., 2019. Sustainable economic development and greenhouse gas emissions: The dynamic impact of renewable energy consumption, GDP, and corruption. *Energies*, 12(17), p.3289.

Wang, S., Zeng, J. and Liu, X., 2019. Examining the multiple impacts of technological progress on CO2 emissions in China: a panel quantile regression approach. *Renewable and Sustainable Energy Reviews*, 103, pp.140-150.

Wen, X., Guo, Y., Wei, Y., and Huang, D. (2014). How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China. *Energy Economics*, *41*, 63-75.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica: *Journal of the Econometric Society*, 817-838.

Wiley, M. and Wiley, J.F., 2019. Univariate Data Visualization. In Advanced R Statistical Programming and Data Models (pp. 1-31). *Apress, Berkeley*, CA.

Xu, M., and Buyya, R. (2020). Managing renewable energy and carbon footprint in multi-cloud computing environments. *Journal of Parallel and Distributed Computing*, *135*, 191-202.

Yaduma, N., Kortelainen, M., and Wossink, A. (2015). The environmental Kuznets curve at different levels of economic development: a counterfactual quantile regression analysis for CO2 emissions. *Journal of Environmental Economics and Policy*, *4*(3), 278-303.

Yan, D., Kong, Y., Ren, X., Shi, Y., and Chiang, S. (2019). The determinants of urban sustainability in Chinese resource-based cities: A panel quantile regression approach. *Science of the Total Environment*, *686*, 1210-1219.

Yu, S., Hu, X., Li, L., and Chen, H. (2020). Does the development of renewable energy promote carbon reduction? Evidence from Chinese provinces. *Journal of Environmental Management*, *268*, 110634.

Zhao, Q. (2000). Restricted regression quantiles. *Journal of Multivariate Analysis*, 72(1), 78-99.

Zhao, X. and Luo, D., 2018. Forecasting fossil energy consumption structure toward low-carbon and sustainable economy in China: Evidence and policy responses. *Energy strategy reviews*, 22, pp.303-312.

Zhu, H., Duan, L., Guo, Y., and Yu, K. (2016). The effects of FDI, economic growth and energy consumption on carbon emissions in ASEAN-5: evidence from panel quantile regression. *Economic Modelling*, *58*, 237-248.

Table 1. Summary statistics and correlations

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | LNREC | LNRGDPC | LNROP | LNCO2PC | LNOGI | LNEGI | LNSGI | LNPGI | LNRC\_EGI | LNREV\_EGI |
| Mean | 0.365827 | 10.15203 | 3.863516 | 2.072413 | 4.268262 | 4.200170 | 4.181932 | 4.422157 | 4.163246 | 4.126055 |
| Median | 0.531485 | 10.31078 | 3.774327 | 2.116788 | 4.345536 | 4.284343 | 4.319608 | 4.487385 | 4.233560 | 4.199472 |
| Maximum | 5.584399 | 11.42538 | 4.776669 | 3.153484 | 4.526195 | 4.577328 | 4.537708 | 4.589186 | 4.547128 | 4.501493 |
| Minimum | -6.907755 | 8.272306 | 2.408746 | 0.118882 | 3.440380 | 3.102938 | 2.975821 | 3.837861 | 3.232802 | 3.254210 |
| Std. Dev. | 2.078497 | 0.668041 | 0.576984 | 0.572280 | 0.221775 | 0.271079 | 0.325246 | 0.157163 | 0.270977 | 0.259287 |
| Skewness | -0.629483 | -0.806743 | -0.095849 | -0.735041 | -1.239142 | -1.235129 | -1.302143 | -1.420951 | -0.932351 | -0.884059 |
| Kurtosis | 3.963194 | 3.014016 | 2.225298 | 3.456151 | 4.075741 | 4.604448 | 3.974588 | 4.186218 | 3.510316 | 3.247932 |
|  | LNREC | LNRGDPC | LNROP | LNCO2PC | LNOGI | LNEGI | LNSGI | LNPGI | LNRC\_EGI | LNREV\_EGI |
| LNREC | 1.000 |  |  |  |  |  |  |  |  |  |
| LNRGDPC | 0.3729 | 1.000 |  |  |  |  |  |  |  |  |
| LNROP | 0.3044 | 0.1478 | 1.000 |  |  |  |  |  |  |  |
| LNCO2PC | 0.2431 | 0.6617 | -0.0020 | 1.000 |  |  |  |  |  |  |
| LNOGI | 0.3591 | 0.7280 | 0.1960 | 0.5630 | 1.000 |  |  |  |  |  |
| LNEGI | 0.2952 | 0.6457 | 0.1840 | 0.4663 | 0.9172 | 1.000 |  |  |  |  |
| LNSGI | 0.3445 | 0.7194 | 0.1838 | 0.5916 | 0.9564 | 0.8355 | 1.000 |  |  |  |
| LNPGI | 0.3504 | 0.5707 | 0.1484 | 0.4296 | 0.8011 | 0.5912 | 0.6777 | 1.000 |  |  |
| LNRC\_EGI | 0.1674 | 0.5609 | 0.1597 | 0.3568 | 0.8604 | 0.9486 | 0.7824 | 0.5376 | 1.000 |  |
| LNREV\_EGI | 0.2826 | 0.7089 | 0.2206 | 0.4497 | 0.8902 | 0.9438 | 0.8025 | 0.6152 | 0.9035 | 1.000 |

Table 2. Unit root tests

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variables | Levin, Lin & Chu t (2002) | | Im, Pesaran and Shin W-stat (2003) | | Breitung t-stat (2005) | |
|  | Statistic | P-value | Statistic | P-value | Statistic | P-value |
| *LNREC* | 3.052 | 0.998 | 1.132 | 0.871 | 3.443 | 0.999 |
| *LNRGDPC* | 1.626 | 0.948 | 1.280 | 0.899 | 2.399 | 0.991 |
| *LNROP* | 1.422 | 0.922 | 0.284 | 0.388 | 2.279 | 0.988 |
| *LNCO2PC* | 1.033 | 0.150 | 3.668 | 0.999 | 3.342 | 0.999 |
| *LNOGI* | 2.217 | 0.986 | 1.561 | 0.997 | 3.715 | 0.999 |
| *LNEGI* | 2.587 | 0.995 | 3.534 | 0.999 | 3.652 | 0.999 |
| *LNSGI* | 0.971 | 0.834 | 0.363 | 0.358 | 1.012 | 0.844 |
| *LNPGI* | 3.631 | 0.999 | 0.809 | 0.209 | 1.117 | 0.986 |
| *LNRC\_EGI* | 2.483 | 0.998 | 1.013 | 0.997 | 0.836 | 0.999 |
| *LNREVEGI* | 10.458 | 0.999 | 1.102 | 0.864 | 2.905 | 0.998 |
| *∆LNREC* | -8.511 | 0.000 | -19.172 | 0.000 | -8.792 | 0.000 |
| *∆LNRGDPC* | -16.006 | 0.000 | -18.294 | 0.000 | -10.379 | 0.000 |
| *∆LNROP* | -31.486 | 0.000 | -23.957 | 0.000 | -9.882 | 0.000 |
| *∆LNCO2PC* | -29.095 | 0.000 | -7.213 | 0.000 | -4.657 | 0.000 |
| *∆LNOGI* | -17.008 | 0.000 | -2.790 | 0.002 | -11.519 | 0.000 |
| *∆LNEGI* | -16.134 | 0.000 | -4.753 | 0.000 | -4.930 | 0.000 |
| *∆LNSGI* | -3.397 | 0.000 | -17.089 | 0.000 | -12.712 | 0.000 |
| *∆LNPGI* | -22.151 | 0.000 | -7.630 | 0.000 | -15.951 | 0.000 |
| *∆LNRC\_EGI* | -16.026 | 0.000 | -3.651 | 0.000 | -6.397 | 0.000 |
| *∆LNREVEGI* | –19.842 | 0.000 | –17.446 | 0.000 | –12.334 | 0.000 |

Table 3. 

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | OLS | White | Rogers | Newey-West | Driscoll-Kraay | OLSMO |
| lnrgdpc | 0.7041\*\*\* | 0.7041\*\*\* | 0.7041\*\*\* | 0.7041 | 0.7041\*\*\* | -1.0728 |
|  | (4.92) | (5.19) | (5.12) | (1.12) | (2.72) | (-0.80) |
| lnrop | 0.8910\*\*\* | 0.8910\*\*\* | 0.8910\*\*\* | 0.8910\*\*\* | 0.8910\*\*\* | 3.6959\*\*\* |
|  | (3.02) | (8.72) | (9.62) | (5.64) | (5.51) | (4.37) |
| lnco2pc | 0.0416 | 0.0416 | 0.0416 | 0.0416 | 0.0416 | 0.0784 |
|  | (0.33) | (0.31) | (0.34) | (0.07) | (0.18) | (0.12) |
| Lnogi | 1.5133\*\*\* | 1.5133\*\*\* | 1.5133\*\*\* | 1.5133 | 1.5133\*\* | 3.8717 |
|  | (2.77) | (4.05) | (4.06) | (1.12) | (2.23) | (1.46) |
| Constant | -16.6824\*\*\* | -16.6824\*\*\* | -16.6824\*\*\* | -16.6824\*\*\* | -16.6824\*\*\* | -17.6918\* |
|  | (-8.95) | (-13.16) | (-14.63) | (-3.70) | (-8.03) | (-1.93) |
| R2 | 0.2168 | 0.2168 | 0.2168 | 0.2168 |  |  |
| N | 1079 | 1079 | 1079 | 1079 | 1079 | 1079 |

Notes. Robust standard errors are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 4. 

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | OLS | White | Rogers | Newey-West | Driscoll-Kraay | OLSMO |
| lnrgdpc | 0.8621\*\*\* | 0.8621\*\*\* | 0.8621\*\*\* | 0.8621 | 0.8621\*\*\* | -1.3839 |
|  | (7.79) | (6.55) | (6.48) | (1.41) | (3.46) | (-1.05) |
| lnrop | 0.9305\*\*\* | 0.9305\*\*\* | 0.9305\*\*\* | 0.9305\*\*\* | 0.9305\*\*\* | 4.1453\*\*\* |
|  | (2.86) | (9.11) | (10.01) | (5.71) | (5.72) | (7.24) |
| lnco2pc | 0.1145 | 0.1145 | 0.1145 | 0.1145 | 0.1145 | -0.6102 |
|  | (0.96) | (0.85) | (0.94) | (0.19) | (0.50) | (-0.91) |
| Lnegi | 0.5848 | 0.5848\*\* | 0.5848\*\* | 0.5848 | 0.5848 | -0.0153 |
|  | (1.43) | (2.12) | (2.30) | (0.62) | (1.25) | (-0.01) |
| Constant | -14.5847\*\*\* | -14.5847\*\*\* | -14.5847\*\*\* | -14.5847\*\*\* | -14.5847\*\*\* | 1.4253 |
|  | (-9.89) | (-13.02) | (-15.11) | (-3.55) | (-8.20) | (0.14) |
| R2 | 0.2081 | 0.2081 | 0.2081 | 0.2081 |  |  |
| N | 1079 | 1079 | 1079 | 1079 | 1079 | 1079 |

Notes. Robust standard errors are in parentheses., \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 5. 

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | OLS | White | Rogers | Newey-West | Driscoll-Kraay | OLSMO |
| lnrgdpc | 0.7699\*\*\* | 0.7699\*\*\* | 0.7699\*\*\* | 0.7699 | 0.7699\*\*\* | -1.1593 |
|  | (4.95) | (5.74) | (5.70) | (1.25) | (3.03) | (-0.97) |
| lnrop | 0.9047\*\*\* | 0.9047\*\*\* | 0.9047\*\*\* | 0.9047\*\*\* | 0.9047\*\*\* | 3.1039\*\*\* |
|  | (2.98) | (8.84) | (9.77) | (5.81) | (5.61) | (5.30) |
| lnco2pc | 0.0184 | 0.0184 | 0.0184 | 0.0184 | 0.0184 | -0.2059 |
|  | (0.13) | (0.13) | (0.14) | (0.03) | (0.08) | (-0.47) |
| Lnsgi | 0.8622\*\* | 0.8622\*\* | 0.8622\*\* | 0.8622 | 0.8622\* | 0.3718 |
|  | (2.10) | (3.30) | (3.18) | (0.91) | (1.75) | (0.10) |
| Constant | -14.5011\*\*\* | -14.5011\*\*\* | -14.5011\*\*\* | -14.5011\*\*\* | -14.5011\*\*\* | 1.2438 |
|  | (-11.78) | (-13.75) | (-14.52) | (-3.40) | (-7.85) | (0.14) |
| R2 | 0.2128 | 0.2128 | 0.2128 | 0.2128 |  |  |
| N | 1079 | 1079 | 1079 | 1079 | 1079 | 1079 |

Notes. Robust standard errors are in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 6. 

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | OLS | White | Rogers | Newey-West | Driscoll-Kraay | OLSMO |
| lnrgdpc | 0.7215\*\*\* | 0.7215\*\*\* | 0.7215\*\*\* | 0.7215 | 0.7215\*\*\* | 0.9420 |
|  | (4.68) | (5.96) | (6.23) | (1.34) | (3.34) | (0.47) |
| lnrop | 0.8911\*\*\* | 0.8911\*\*\* | 0.8911\*\*\* | 0.8911\*\*\* | 0.8911\*\*\* | 1.5247\* |
|  | (3.11) | (8.90) | (9.94) | (5.60) | (5.71) | (1.93) |
| lnco2pc | 0.0621 | 0.0621 | 0.0621 | 0.0621 | 0.0621 | -0.1806 |
|  | (0.55) | (0.47) | (0.52) | (0.11) | (0.28) | (-0.52) |
| Lnpgi | 2.7504\*\*\* | 2.7504\*\*\* | 2.7504\*\*\* | 2.7504\* | 2.7504\*\*\* | 2.4036 |
|  | (3.13) | (6.51) | (5.87) | (1.91) | (3.34) | (0.64) |
| Constant | -22.6059\*\*\* | -22.6059\*\*\* | -22.6059\*\*\* | -22.6059\*\*\* | -22.6059\*\*\* | -23.7914\*\* |
|  | (-6.10) | (-13.23) | (-12.25) | (-3.70) | (-6.89) | (-1.99) |
| R2 | 0.2350 | 0.2350 | 0.2350 | 0.2350 |  |  |
| N | 1079 | 1079 | 1079 | 1079 | 1079 | 1079 |

Robust standard errors are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 7. 

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | OLS | White | Rogers | Newey-West | Driscoll-Kraay | OLSMO |
| lnrgdpc | 1.0966\*\*\* | 1.0966\*\*\* | 1.0966\*\*\* | 1.0966\* | 1.0966\*\*\* | -0.9740 |
|  | (10.00) | (8.57) | (8.76) | (1.93) | (4.67) | (-0.78) |
| lnrop | 0.9785\*\* | 0.9785\*\*\* | 0.9785\*\*\* | 0.9785\*\*\* | 0.9785\*\*\* | 4.0017\*\*\* |
|  | (2.69) | (9.58) | (10.53) | (5.92) | (6.02) | (11.73) |
| lnco2pc | 0.1193 | 0.1193 | 0.1193 | 0.1193 | 0.1193 | -0.5442 |
|  | (1.05) | (0.88) | (0.98) | (0.20) | (0.52) | (-0.78) |
| lnrc\_egi | -0.4644 | -0.4644\* | -0.4644\*\* | -0.4644 | -0.4644 | -0.1958 |
|  | (-1.04) | (-1.83) | (-2.05) | (-0.59) | (-1.10) | (-0.22) |
| Constant | -12.7665\*\*\* | -12.7665\*\*\* | -12.7665\*\*\* | -12.7665\*\*\* | -12.7665\*\*\* | -2.1356 |
|  | (-7.80) | (-11.35) | (-12.61) | (-2.90) | (-6.80) | (-0.20) |
| R2 | 0.2073 | 0.2073 | 0.2073 | 0.2073 |  |  |
| N | 1079 | 1079 | 1079 | 1079 | 1079 | 1079 |

Robust standard errors are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 8. 

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | OLS | White | Rogers | Newey-West | Driscoll-Kraay | OLSMO |
| lnrgdpc | 1.1484\*\*\* | 1.1484\*\*\* | 1.1484\*\*\* | 1.1484\* | 1.1484\*\*\* | -0.3339 |
|  | [8.46] | [8.17] | [8.02] | [1.80] | [4.29] | [-0.25] |
| lnrop | 0.9903\*\* | 0.9903\*\*\* | 0.9903\*\*\* | 0.9903\*\*\* | 0.9903\*\*\* | 0.4646\* |
|  | [2.71] | [9.62] | [10.57] | [6.04] | [6.06] | [1.85] |
| lnco2pc | 0.0966 | 0.0966 | 0.0966 | 0.0966 | 0.0966 | -0.9327\*\*\* |
|  | [0.95] | [0.71] | [0.77] | [0.16] | [0.41] | [-3.66] |
| lnrevegi | -0.0004 | -0.0004\* | -0.0004\* | -0.0004 | -0.0004 | -0.0001 |
|  | [-1.04] | [-1.90] | [-1.90] | [-0.50] | [-1.03] | [-0.08] |
| Constant | -14.959\*\*\* | -14.959\*\*\* | -14.959\*\*\* | -14.9593\*\*\* | -14.9593\*\*\* | 5.0264 |
|  | [-12.62] | [-12.04] | [-11.70] | [-2.82] | [-6.30] | [0.53] |
| R2 | 0.2075 | 0.2075 | 0.2075 | 0.2075 |  |  |
| N | 1079 | 1079 | 1079 | 1079 | 1079 | 1079 |

Robust standard errors are in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 9. Machado and Silva Panel Quantile regression (2019) 

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| VARIABLES | 0.05 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 0.95 |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Lnrgdpc | 1.4582\*\*\* | 0.4621\* | 0.0785 | 0.3594\*\*\* | 0.7187\*\*\* | 0.9013\*\*\* | 0.9230\*\*\* | 0.8555\*\*\* | 0.8603\*\*\* | 0.3830\*\*\* | 0.1918\* |
|  | (0.4488) | (0.2603) | (0.1531) | (0.1316) | (0.1223) | (0.1144) | (0.1048) | (0.1451) | (0.1439) | (0.1329) | (0.1064) |
| Lnrop | 1.1815\*\*\* | 0.9263\*\*\* | 0.9104\*\*\* | 0.8263\*\*\* | 0.8355\*\*\* | 0.9378\*\*\* | 0.9440\*\*\* | 0.8383\*\*\* | 1.0265\*\*\* | 1.0828\*\*\* | 0.8662\*\*\* |
|  | (0.3306) | (0.2242) | (0.1209) | (0.1206) | (0.1124) | (0.0924) | (0.0882) | (0.1109) | (0.1132) | (0.0415) | (0.0997) |
| lnco2pc | -1.9788\*\*\* | -0.4882 | 0.0306 | 0.0123 | -0.0710 | -0.1656 | -0.0692 | 0.0925 | 0.2021 | 1.1691\*\*\* | 1.0601\*\*\* |
|  | (0.5712) | (0.3254) | (0.1570) | (0.1485) | (0.1422) | (0.1249) | (0.1192) | (0.1475) | (0.1578) | (0.1891) | (0.1364) |
| Lnogi | 2.7392\* | 3.0907\*\*\* | 2.8484\*\*\* | 2.6137\*\*\* | 2.1967\*\*\* | 1.8253\*\*\* | 1.2211\*\*\* | 0.8956\*\* | 0.4028 | 0.5324 | 1.0241\*\*\* |
|  | (1.6356) | (1.0300) | (0.4112) | (0.3951) | (0.3975) | (0.3700) | (0.3695) | (0.4258) | (0.5783) | (0.3649) | (0.2637) |
| Constant | -30.329\*\*\* | -22.095\*\*\* | -17.343\*\*\* | -18.267\*\*\* | -19.510\*\*\* | -19.582\*\*\* | -17.145\*\*\* | -14.573\*\*\* | -12.962\*\*\* | -5.463\*\*\* | -8.475\*\*\* |
|  | (3.8818) | (2.9644) | (1.3285) | (1.4032) | (1.4134) | (1.2769) | (1.1859) | (1.4155) | (1.8596) | (0.9218) | (1.3039) |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Observations | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 |
| Robust standard errors are in parentheses. | | |  |  |  |  |  |  |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. | | | | | | | | | | | |

Table 10. Machado and Silva Panel Quantile regression (2019) 

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| VARIABLES | 0.05 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 0.95 |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Lnrgdpc | 1.7672\*\*\* | 1.0359\*\*\* | 0.4565\*\*\* | 0.3910\*\* | 0.6781\*\*\* | 0.8337\*\*\* | 0.9342\*\*\* | 0.9696\*\*\* | 0.9399\*\*\* | 0.3423\*\* | 0.1632\*\* |
|  | (0.2435) | (0.2705) | (0.1519) | (0.1667) | (0.1335) | (0.1052) | (0.1020) | (0.1412) | (0.1330) | (0.1487) | (0.0819) |
| Lnrop | 0.9880\*\*\* | 0.8954\*\*\* | 0.8588\*\*\* | 0.8295\*\*\* | 0.7526\*\*\* | 0.8940\*\*\* | 0.9287\*\*\* | 0.8799\*\*\* | 1.0196\*\*\* | 1.0618\*\*\* | 0.9943\*\*\* |
|  | (0.2683) | (0.1516) | (0.1147) | (0.1271) | (0.1085) | (0.0849) | (0.0861) | (0.1123) | (0.1123) | (0.0873) | (0.0646) |
| lnco2pc | -1.4668\*\* | -0.1803 | 0.2843\* | 0.2802\* | 0.0470 | -0.0215 | -0.0072 | 0.0771 | 0.1895 | 1.1848\*\*\* | 1.2863\*\*\* |
|  | (0.6659) | (0.2900) | (0.1495) | (0.1604) | (0.1306) | (0.1157) | (0.1200) | (0.1522) | (0.1557) | (0.2155) | (0.0895) |
| Lnegi | -0.7648 | -0.4120 | 0.9041\*\*\* | 1.5232\*\*\* | 1.6807\*\*\* | 1.4481\*\*\* | 1.0076\*\*\* | 0.6124\* | 0.1321 | -0.5224\*\* | -0.0051 |
|  | (0.7291) | (0.4282) | (0.2284) | (0.2801) | (0.2714) | (0.2509) | (0.2624) | (0.3382) | (0.4290) | (0.2645) | (0.2215) |
| Constant | -18.461\*\*\* | -13.595\*\*\* | -13.136\*\*\* | -14.369\*\*\* | -16.675\*\*\* | -17.314\*\*\* | -16.354\*\*\* | -14.623\*\*\* | -12.533\*\*\* | -5.0689\*\*\* | -4.8630\*\*\* |
|  | (2.9146) | (1.7248) | (1.0340) | (1.2626) | (1.0330) | (1.0093) | (1.0318) | (1.3498) | (1.6394) | (0.8424) | (1.0341) |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Observations | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 |
| Robust standard errors are in parentheses. | | |  |  |  |  |  |  |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. | | | | | | | | | | | |

Table 11. Machado and Silva Panel Quantile regression (2019) 

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| VARIABLES | 0.05 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 0.95 |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Lnrgdpc | 1.5309\*\*\* | 0.4135 | 0.1677 | 0.5030\*\*\* | 0.8970\*\*\* | 1.0715\*\*\* | 1.1076\*\*\* | 1.1505\*\*\* | 0.8656\*\*\* | 0.3758\*\* | 0.2387 |
|  | (0.5534) | (0.2817) | (0.1571) | (0.0844) | (0.0851) | (0.1082) | (0.0960) | (0.1446) | (0.1522) | (0.1713) | (0.1613) |
| Lnrop | 1.0494\*\* | 0.9284\*\*\* | 0.8801\*\*\* | 0.9659\*\*\* | 0.8369\*\*\* | 0.9733\*\*\* | 0.9122\*\*\* | 0.9154\*\*\* | 1.0281\*\*\* | 1.0808\*\*\* | 0.7119\*\*\* |
|  | (0.4075) | (0.2338) | (0.1270) | (0.1136) | (0.1158) | (0.1004) | (0.0882) | (0.1102) | (0.1162) | (0.0895) | (0.1067) |
| lnco2pc | -1.7297\*\*\* | -0.4135 | -0.0023 | -0.1109 | -0.2551\* | -0.2417\* | -0.0145 | 0.0089 | 0.1961 | 1.1668\*\*\* | 1.0103\*\*\* |
|  | (0.6048) | (0.3487) | (0.1828) | (0.1403) | (0.1498) | (0.1424) | (0.1241) | (0.1486) | (0.1558) | (0.1786) | (0.1586) |
| Lnsgi | 2.2662 | 1.8832\*\*\* | 1.8372\*\*\* | 1.5699\*\*\* | 1.2347\*\*\* | 0.8281\*\*\* | 0.3119 | 0.0136 | 0.2158 | 0.3292 | 0.8027\*\*\* |
|  | (1.4648) | (0.7273) | (0.3488) | (0.2422) | (0.2972) | (0.2927) | (0.2616) | (0.2844) | (0.4048) | (0.2612) | (0.2027) |
| Constant | -28.915\*\*\* | -16.390\*\*\* | -13.626\*\*\* | -15.429\*\*\* | -16.777\*\*\* | -16.954\*\*\* | -15.050\*\*\* | -13.911\*\*\* | -12.183\*\*\* | -6.2768\*\*\* | -7.2878\*\*\* |
|  | (2.7906) | (1.9349) | (1.2192) | (0.9999) | (1.0973) | (1.0510) | (0.8951) | (1.1346) | (1.2814) | (0.9223) | (1.3185) |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Observations | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 |
| Robust standard errors are in parentheses. | | |  |  |  |  |  |  |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. | | | | | | | | | | | |

Table 12. The Machado and Silva Panel Quantile regression (2019) 

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| VARIABLES | 0.05 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 0.95 |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Lnrgdpc | 1.1358\*\*\* | 0.5941\*\*\* | 0.3741\*\* | 0.6104\*\*\* | 0.8564\*\*\* | 1.0468\*\*\* | 0.9315\*\*\* | 0.8582\*\*\* | 0.5998\*\*\* | 0.0879 | 0.1018 |
|  | (0.2619) | (0.1563) | (0.1496) | (0.1153) | (0.0964) | (0.1175) | (0.1003) | (0.1020) | (0.1383) | (0.1249) | (0.1287) |
| Lnrop | 0.9243\*\*\* | 0.9127\*\*\* | 0.9103\*\*\* | 0.8305\*\*\* | 0.9223\*\*\* | 1.0026\*\*\* | 0.9093\*\*\* | 0.7474\*\*\* | 0.8455\*\*\* | 0.9600\*\*\* | 0.8573\*\*\* |
|  | (0.2052) | (0.1724) | (0.1302) | (0.1160) | (0.1117) | (0.0992) | (0.0887) | (0.0941) | (0.1235) | (0.1290) | (0.1080) |
| lnco2pc | -1.7227\*\*\* | -0.6709\*\*\* | 0.0707 | 0.0269 | 0.0079 | -0.0080 | 0.0628 | 0.0472 | 0.2369 | 1.2849\*\*\* | 1.0581\*\*\* |
|  | (0.3915) | (0.2383) | (0.1842) | (0.1426) | (0.1320) | (0.1360) | (0.1086) | (0.1188) | (0.1677) | (0.2181) | (0.1408) |
| Lnpgi | 6.5028\*\*\* | 6.3676\*\*\* | 4.4043\*\*\* | 3.6803\*\*\* | 3.2948\*\*\* | 1.7310\*\*\* | 1.8336\*\*\* | 2.3183\*\*\* | 2.3810\*\*\* | 1.2184\*\* | 1.8322\*\*\* |
|  | (0.9881) | (1.0596) | (0.6991) | (0.5637) | (0.6193) | (0.5914) | (0.2875) | (0.3535) | (0.6129) | (0.4898) | (0.4436) |
| Constant | -43.076\*\*\* | -38.081\*\*\* | -27.803\*\*\* | -25.990\*\*\* | -26.630\*\*\* | -21.467\*\*\* | -20.228\*\*\* | -20.580\*\*\* | -18.571\*\*\* | -9.886\*\*\* | -11.282\*\*\* |
|  | (3.2864) | (3.9090) | (2.7251) | (2.3573) | (2.6091) | (2.3473) | (1.2075) | (1.4066) | (2.3599) | (2.2735) | (2.0415) |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Observations | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 |
| Notes. Robust standard errors are in parentheses. | | |  |  |  |  |  |  |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. | | | | | | | | | | | |

Table13. Machado and Silva Panel Quantile regression (2019) 

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| VARIABLES | 0.05 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 0.95 |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Lnrgdpc | 1.8406\*\*\* | 1.1203\*\*\* | 0.6821\*\*\* | 0.5947\*\*\* | 1.0062\*\*\* | 1.1484\*\*\* | 1.3151\*\*\* | 1.3103\*\*\* | 1.0911\*\*\* | 0.5867\*\*\* | 0.9069\*\*\* |
|  | (0.2030) | (0.2058) | (0.1643) | (0.1598) | (0.1168) | (0.1201) | (0.1016) | (0.1170) | (0.1320) | (0.1252) | (0.1079) |
| Lnrop | 0.8467\*\*\* | 0.9326\*\*\* | 0.9311\*\*\* | 0.8980\*\*\* | 0.8982\*\*\* | 0.9626\*\*\* | 0.9221\*\*\* | 1.0738\*\*\* | 0.9739\*\*\* | 1.2447\*\*\* | 1.0267\*\*\* |
|  | (0.2278) | (0.1611) | (0.1335) | (0.1326) | (0.1217) | (0.0980) | (0.0850) | (0.0997) | (0.0905) | (0.1198) | (0.1004) |
| lnco2pc | -1.1643\* | -0.0870 | 0.3596\*\* | 0.3753\*\* | 0.0171 | -0.0789 | -0.0348 | 0.0375 | 0.2397\* | 0.9282\*\*\* | 0.7401\*\*\* |
|  | (0.6336) | (0.2265) | (0.1804) | (0.1637) | (0.1267) | (0.1335) | (0.1206) | (0.1338) | (0.1410) | (0.1769) | (0.1032) |
| lnrc\_egi | -1.7671\*\* | -0.9742\*\* | 0.0673 | 0.2899 | 0.5196\* | 0.3540 | -0.2767 | -0.7250\*\* | -1.2700\*\*\* | -2.1051\*\*\* | -2.8734\*\*\* |
|  | (0.8981) | (0.3852) | (0.3237) | (0.3067) | (0.2914) | (0.2768) | (0.2665) | (0.3032) | (0.3902) | (0.4786) | (0.2321) |
| Constant | -14.976\*\*\* | -12.477\*\*\* | -12.421\*\*\* | -11.787\*\*\* | -15.607\*\*\* | -15.988\*\*\* | -14.674\*\*\* | -13.112\*\*\* | -8.0944\*\*\* | -1.1761 | 0.4685 |
|  | (3.1672) | (1.2390) | (1.3706) | (1.3643) | (0.9715) | (1.1597) | (1.0978) | (1.2096) | (1.5638) | (1.7488) | (1.2372) |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Observations | 1,079 | 1,079 | 1,079 | 1,07z9 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 |
| Robust standard errors are in parentheses | | |  |  |  |  |  |  |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | | | | | | | | |

Table14. Machado and Silva Panel Quantile regression (2019) 

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| VARIABLES | 0.05 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 0.95 |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Lnrgdpc | 1.8341\*\*\* | 1.1175\*\*\* | 0.6475\*\*\* | 0.5537\*\*\* | 0.9346\*\*\* | 1.0992\*\*\* | 1.3028\*\*\* | 1.4792\*\*\* | 1.2547\*\*\* | 0.9428\*\*\* | 1.3244\*\*\* |
|  | (0.2343) | (0.2372) | (0.1869) | (0.1851) | (0.1275) | (0.1155) | (0.0786) | (0.1220) | (0.1391) | (0.1523) | (0.1647) |
| Lnrop | 0.9257\*\*\* | 0.9268\*\*\* | 0.9536\*\*\* | 0.8643\*\*\* | 0.8356\*\*\* | 0.9546\*\*\* | 0.9220\*\*\* | 1.0375\*\*\* | 1.0233\*\*\* | 1.2336\*\*\* | 1.1293\*\*\* |
|  | (0.2945) | (0.1881) | (0.1370) | (0.1331) | (0.1189) | (0.0943) | (0.0366) | (0.0967) | (0.1187) | (0.1315) | (0.1203) |
| lnco2pc | -1.2142\*\* | -0.1072 | 0.3481\* | 0.4191\*\* | 0.0080 | -0.0019 | -0.0436 | -0.0867 | 0.0467 | 0.7730\*\*\* | 0.5166\*\*\* |
|  | (0.6118) | (0.2455) | (0.1816) | (0.1672) | (0.1211) | (0.1338) | (0.1204) | (0.1362) | (0.1520) | (0.1950) | (0.1319) |
| Lnrevegi | -0.0013\*\* | -0.0007\* | 0.0001 | 0.0003 | 0.0006\*\*\* | 0.0002 | -0.0002 | -0.0007\*\*\* | -0.0010\*\*\* | -0.0014\*\*\* | -0.0016\*\*\* |
|  | (0.0006) | (0.0004) | (0.0003) | (0.0003) | (0.0002) | (0.0002) | (0.0001) | (0.0002) | (0.0003) | (0.0002) | (0.0002) |
| Constant | -21.631\*\*\* | -15.895\*\*\* | -11.932\*\*\* | -10.347\*\*\* | -12.885\*\*\* | -14.300\*\*\* | -15.556\*\*\* | -16.926\*\*\* | -14.136\*\*\* | -12.278\*\*\* | -14.520\*\*\* |
|  | (1.8332) | (1.9714) | (1.6518) | (1.5752) | (1.0992) | (1.0106) | (0.5452) | (1.1093) | (1.3571) | (1.3544) | (1.3665) |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Observations | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 | 1,079 |
| Robust standard errors are in parentheses. | | |  |  |  |  |  |  |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05\*p<0.1. | |  |  |  |  |  |  |  |  |  |  |

Appendix A1: Cross sectional dependence test.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variables | Breusch-Pagan LM | Pesaran scaled LM | Bias-corrected scaled LM | Pesaran CD |
|  |  |  |  |  |
| *LNREC* | 10059.25\*\*\* | 326.2925\*\*\* | 325.9592\*\*\* | 98.53908\*\*\* |
| *LNRGDPC* | 15615.43\*\*\* | 514.6649\*\*\* | 514.3315\*\*\* | 123.5521\*\*\* |
| *LNROP* | 17108.00\*\*\* | 565.2676\*\*\* | 564.9343\*\*\* | 129.7603\*\*\* |
| *LNCO2PC* | 7089.907\*\*\* | 225.6225\*\*\* | 225.2891\*\*\* | 28.47142\*\*\* |
| *LNOGI* | 15332.66\*\*\* | 505.0781\*\*\* | 504.7448\*\*\* | 122.2097\*\*\* |
| *LNEGI* | 13957.28\*\*\* | 458.4483\*\*\* | 458.1150\*\*\* | 113.2989\*\*\* |
| *LNSGI* | 13665.48\*\*\* | 448.5554\*\*\* | 448.2221\*\*\* | 115.5948\*\*\* |
| *LNPGI* | 9655.907\*\*\* | 312.6180\*\*\* | 312.2847\*\*\* | 91.13016\*\*\* |
| *LNRC\_EGI* | 13179.78\*\*\* | 432.0885\*\*\* | 431.7552\*\*\* | 108.0582\*\*\* |
| *LNREVEGI* | 15332.27\*\*\* | 505.0649\*\*\* | 504.7315\*\*\* | 121.8918\*\*\* |

Note: \*\*\* p<0.01

1. <https://www.iea.org/reports/renewables-information-2019> [↑](#footnote-ref-2)
2. Tax benefits, rebates and tariffs. [↑](#footnote-ref-3)
3. Economic, social, political and overall globalization developed by Dreher (2006) [↑](#footnote-ref-4)
4. The reconstructed economic globalization comprises economic globalization index by adding the real trade openness instead of the nominal trade openness that enhances the economic globalization index of Dreher (2006) by using new variables, such as the trade partner diversification, international debt, and international reserves (Gozgor,(2018). [↑](#footnote-ref-5)
5. This revisited economic globalization index is developed by Gygli et *al.,* (2019) that enriches the economic globalization index of Dreher (2006) by adding the trade partner diversification, foreign debt, international reserves, etc. [↑](#footnote-ref-6)
6. This method is advanced then traditional quantile regression such as Koenker and Bassett (1978); Koenker (2004); Lamarche (2010); Galvao (2011) and Canay (2011) because traditional methods suffer from under and over-estimating of coefficient. [↑](#footnote-ref-7)
7. Pollution-intensive productions in developed countries make strict environmental regulations that must shift to developing countries with the less-environmental regulations (Copeland and Taylor, 2004). [↑](#footnote-ref-8)
8. See Sener et *al.,* (2018) for a brief literature review that investigates the drivers and barriers of renewable energy deployment in various countries. [↑](#footnote-ref-9)
9. Data will be shared as per the request of the authors. [↑](#footnote-ref-10)
10. Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States. [↑](#footnote-ref-11)
11. The check function is a loss function that retrieves the -th sample quantile (for details refer to Qunantile Regression (2005), Section 1.3, by Roger Koenker). [↑](#footnote-ref-12)