Do economic policy uncertainty and geopolitical risk surge CO_2 emissions? New insights from panel quantile regression approach

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Abstract

In recent times, economic policy uncertainty and geopolitical risk have escalated exponentially, and these factors affect both the economy and the environment. Therefore, the objective of this study is to investigate whether economic policy uncertainty and geopolitical risk impede CO_2 emissions in BRICST countries. We employ second generation panel data methods, AMG and CCEMG estimator, and panel quantile regression model. We find that all variables are integrated at I (1), and there exists co-integration among considered variables of the study. Moreover, we note that economic policy uncertainty and geopolitical risk have a heterogeneous impact on CO_2 emissions across different quantiles. Economic policy uncertainty adversely affects CO_2 emissions at lower and middle quantiles, while it surges the CO_2 emissions at higher quantiles. On the contrary, geopolitical risk surges CO_2 emissions at lower quartiles, and it plunges CO_2 emissions at middle and higher quantiles. Further, GDP per capita, non-renewable energy, renewable energy, and urbanization also have a heterogeneous impact on CO_2 emissions in the conditional distribution of CO_2 emissions. Based on the results, policy direction was discussed.

Keywords: Economic policy uncertainty; geopolitical risk; renewable energy; non-renewable energy; panel quantile regression; BRICST countries

1. Introduction

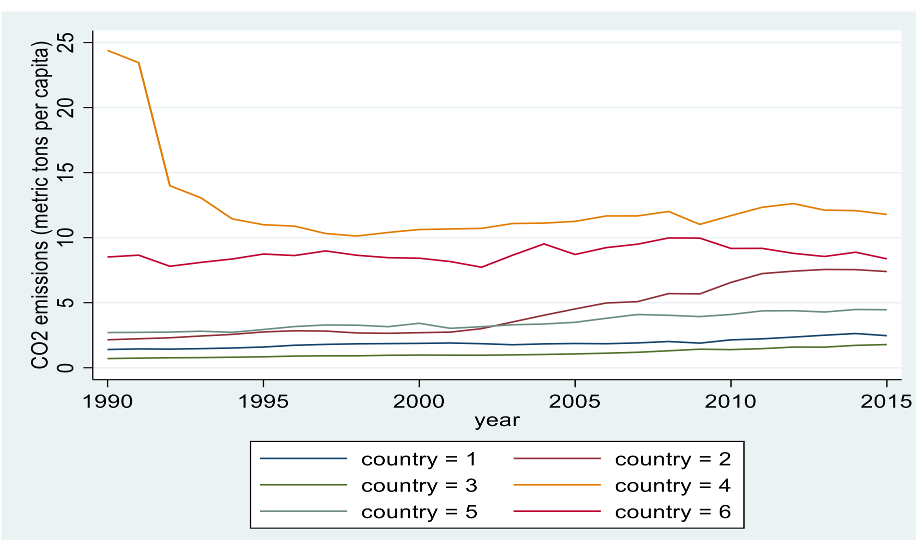
In the energy and environmental debate, carbon dioxide (CO_2) often leads to negative consequences on natural and human activities. This is not all-time true, because CO_2 has its important roles being exercised on natural and human events. Like the air we exhale, the nutrition we consumed, and the product we buy. In addition, CO_2 is discharged when plants and animal inhale oxygen and nature such as ecosystem maintain the situation by absorbing and consequently eradicating the CO_2 through plants and oceans. However, when an excess of CO_2 is emitted by human activities on earth, it often causes damage to the environment, thereby leading to climate change or global warming. At this stage, CO_2, like other greenhouse gases (methane, and water vapour, etc.), holds heat from escaping from the atmosphere, and thus the systematic pattern of weather is disrupted, global temperature is increased, and other climate changes occurred. CO_2 emission is caused through different means of activities from individuals, services or events, government, organization, etc. This is emitted through deforestation, burning of fossil fuels, civil construction, transportation, government and commercial industry, manufacturing of foods, and other services. All these are needed for the sustainable economic growth of a country, and if stopped could posed threat to the global economy, giving rise to concerns on climate change, political and policy uncertainty.

Fighting to reduce greenhouse gas emissions, especially CO_2, is fighting against nature, it required no transport or permission to contribute to environmental problems everywhere, it is a threat to human life, and even a major cause of economic instability and jeopardized the nation's security. Nonetheless, the environmental changes, according to Antonakakis et al. (2017), are associated with all man-made activities, such as the burning of fossil fuel for energy use, pitched toward economic growth, thereby actuating adverse effects to the quality of the environment.

This means that, even, a nation will continue to develop through the consumption of certain energy through government and commercial industry. For instance, in figure 1 below which represent the CO_2 consumption in BRICST countries, it was observed that increase, in metric tons, from the start of 1990 till 2015. In the lieu of this, previous scholars have been investigated the problem, for decades, for the proper maintenance of sustainable development growth across the globe.

Fossil energy utilization is normally seen as the lead cause of extreme carbon dioxide emission issues, and diminishing its consumption is a required process for both industrial and non-industrial nations to address the environmental change issue. In any case, because of the acknowledged view that energy utilization is perhaps the main driver of monetary development (WEF, 2018), the execution of energy measures have raised significant worries for financial development. In particular, assuming energy utilization causes fossil fuel byproducts yet is needed for monetary development, receiving energy preservation approaches will give numerous nations the issue of picking between the "climate or the economy.

Figure 1. The trend of CO_2 emissions



Note: "Country 1" represents South Africa, "country 2" denotes Brazil, "country 3" is Turkey, "country 4" represents China, "country 5" denotes India, and "country 6" is Russia.

Over the years, several studies have revisited the relationship between economic growth, greenhouse gas emission, energy consumption (renewable and nonrenewable energy), but their findings are conflicting (Liu et al., 2019). The conflicting outcomes had made many countries choose different energy policies. For instance, Kraft and Kraft (1978), Menegaki (2010), and Rahman and Kashem (2017) posited in their study, specified by the energy conservation hypothesis, that energy consumption does not prompt economic growth. For this reason, policies can promote the reduction of CO_2 without taking into consideration, its adverse effect on economic growth. On the other side, the economic led-growth hypothesis study by Appiah (2018), Cai et al. (2018), and Ha et al. (2018) revealed that energy consumption is consistent with economic growth.

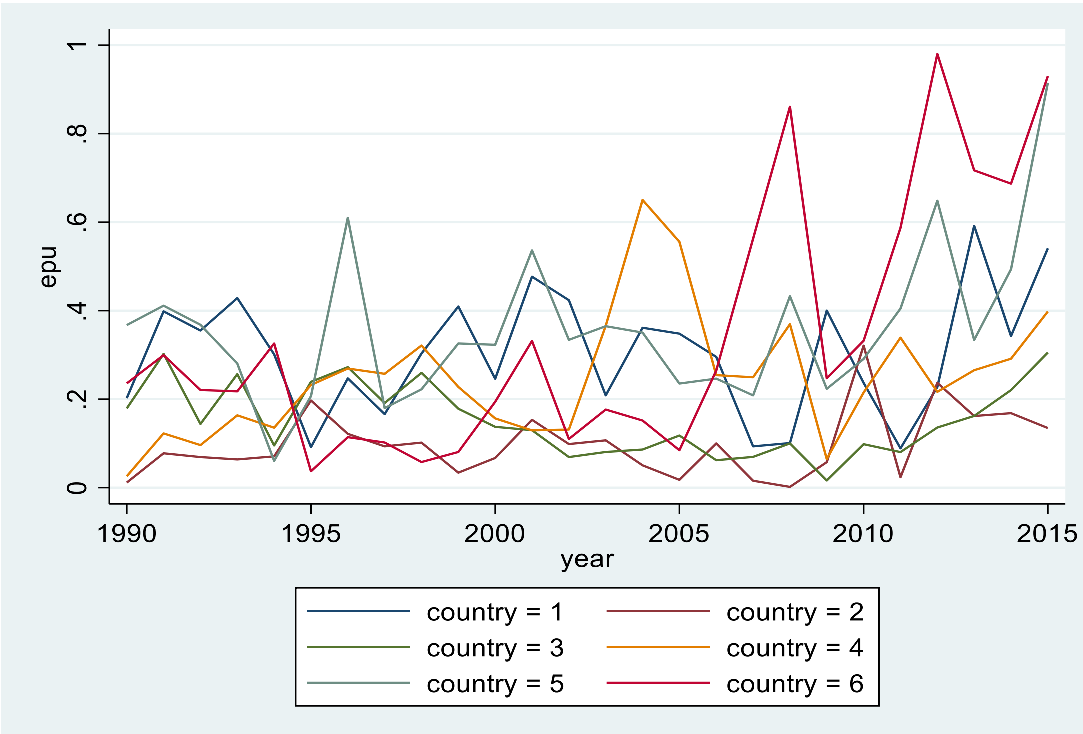
Consequently, policy implications might face environmental or economic problems, because controlling energy consumption may hinder economic growth. Moreover, an increase in CO_2 emission resulting from economic growth means that at the expense of the environment, economic growth is realized (Shahbaz, 2016; Mirza and Kanwal, 2017), thus lowering the CO_2 emission to make economic growth ecologically friendly will be the priority of policy direction in such case (Liu et al., 2019). Consequently, an exact understanding of the driver of carbon emissions and economic growth is essential for policy authorities to cautiously design proper administration guidelines that can help their nations realize the win-win of the climate and the economy. With these, this paper attempt to identify the economic growth-emission nexus while considering two uncertainties – economic policy uncertainty (EPU) and geopolitical risk (GPR) in the BRICST countries for a period of 1990 – 2015. The literature claimed that the behaviour of the economic agent, delay in consumption decision, and investment are influenced by these uncertainties.

EPU, according to the description of Jin et al. (2019), is portrayed as the vulnerability related to spikes in government administrative, financial, and monetary strategies that change the climate wherein people and organizations work. Different evidence from the empirical study has revealed that higher EPU is a yardstick for effect in economic growth, tourism, financial development, investment, inflations, and other macroeconomic variables (Ashraf and Shen, 2019; Jin et al. 2019; Akron et al., 2020). Also, EPU is associated with vulnerabilities relating to monetary, fiscal, trade, and other interrelated policies (Tiwari et al., 2019). Next, there exist three strands of literature related to the EPU-environment nexus. The first strand confirms that EPU increases environmental degradation (Anser et al., 2021a; Anser et al., 2021c), while the second strand of related literature documents that EPU decreases environmental degradation (Syed and Bouri, 2021; Chen et al., 2021). Parallel to this, the third strand of EPU-environment nexus expounds that EPU does not affect the environment (Abbasi and Adedoyin, 2021). These aforementioned contrasting conclusions are confusing for policymakers at the time of any policy proposal, therefore, the vague relationship between EPU and environment propels us to reinvestigate the EPU-environment relationship to reach a particular conclusion, and to complement the prior studies. Defining GPR is associated with political hullaballoo, discrepancy, hostile issues, and it is perceived as a yardstick for change in the business cycle (Tiwari et al., 2019). There are two dimensions of GPR-environment literature. One shows that GPR upsurges environmental pollution (Anser et al., 2021b), whereas the other reports that GPR improves environmental quality (Anser et al., 2021c). The vague relationship between GPR and the environment calls for further probing for clear policy implementations, which motivates this study.

Based on the above milieu, the objective of this study is to explore the impact of EPU and GPR on CO_2 emissions in the case of BRICST countries. It is well known that BRICST countries are among the top emerging countries with significantly high economic growth rates with the consort of higher CO_2 emissions (Erdogan et al., 2019). So, it is inevitable to explore the drivers of carbon emissions in the case of BRICST countries. Therefore, we are interested to know whether the trend in EPU (figure 2) and GPR (figure 3) for the period of 1990 – 2015 have a significant association with emissions and if so, we are keen to know whether the relationship surges or diminish the emission.

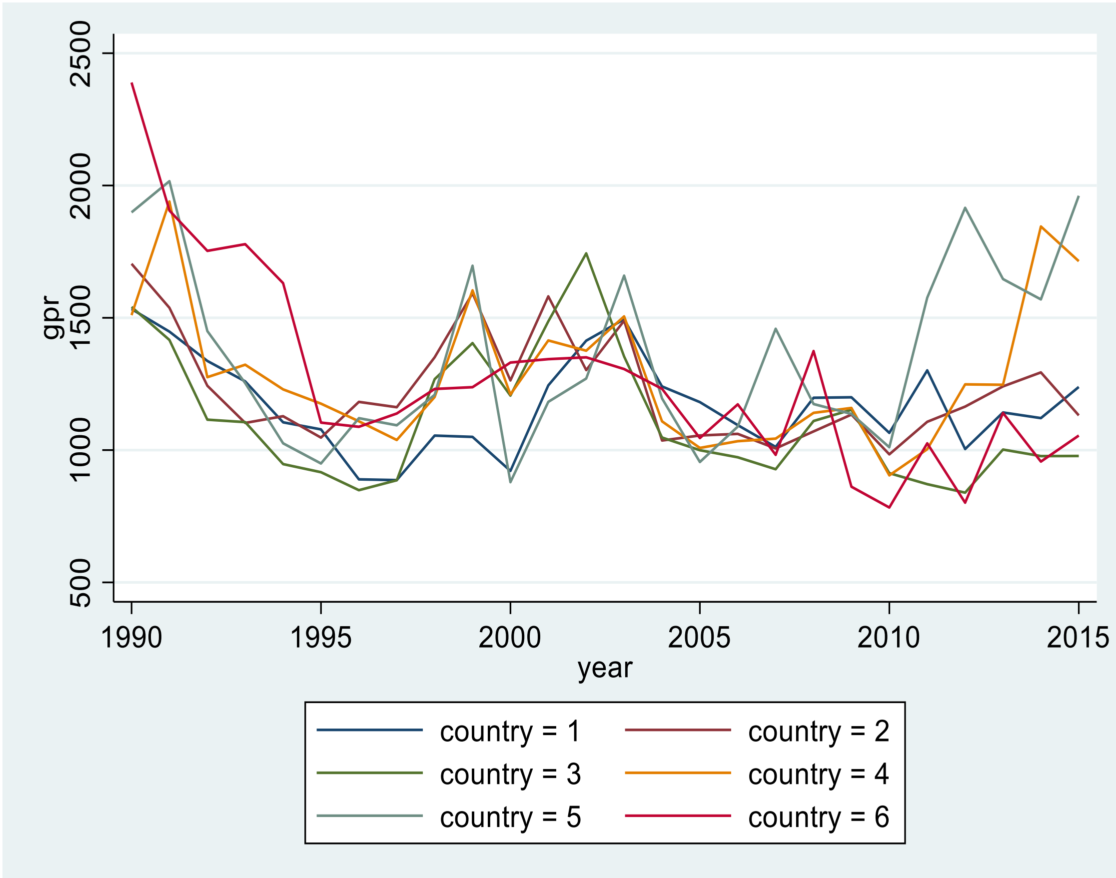
Regarding the uniqueness of this study, to the best of our knowledge, this is the first paper to consider the effect of EPU and GPR in panel emission of BRICST countries. Further, this is the first study that employs the panel quantile regression approach, in consort with AMG and CCMG estimators, to evaluate the effect of EPU and GPR on carbon emissions. Panel quantile regression outperforms mean-based regression models since it covers individual heterogeneity and distributional heterogeneity. That is, panel quantile regression allows probing the effect of EPU and GPR on high-, average-, and low-emitter countries.

Figure 2. The trend of EPU



Note: "Country 1" represents South Africa, "country 2" denotes Brazil, "country 3" is Turkey, "country 4" represents China, "country 5" denotes India, and "country 6" is Russia.

Figure 3. The trend of GPR



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2. Literature review

We divide this section into two subsections. The first subsection reports the existed studies on the impact of EPU and/ or GPR on CO_2 emissions, whereas the second subsection highlights the prior literature on the socio-economic determinants of CO_2 emissions using panel quantile regression.

2.1 Economic policy uncertainty, geopolitical risk, and CO_2 emissions

In their seminal study on the relationship between EPU and CO_2 emissions, Jiang et al. (2019) employ Granger causality to probe the effect of EPU on sector-wise CO_2 emissions for the US. The findings from the study note that uni-directional causality running from EPU to CO_2 emissions. After the study of Jiang et al. (2019), several studies explore the impact of EPU on environmental degradation, and they have not yet reached any conclusion. For instance, one group of studies reports that EPU escalates CO_2 emissions, and the other group notes that EPU plunges the emissions. For instance, Danish et al. (2020) apply dynamic ARDL methodology to investigate the dynamic relationship between EPU and CO_2 emissions in the US. The findings from their study highlight that EPU leads to higher CO_2 emissions. Next, Pirgaip and Dinçergök (2020) noted that EPU raises the level of CO_2 emissions in the case of G7 countries. Moreover, Wang et al. (2020) use the world uncertainty index (WUI) as a proxy of EPU and highlight that EPU contributes to CO_2 emissions.

Recently, Anser et al. (2021a) use a panel ARDL approach to examine the effect of EPU (measured by world uncertainty index) on CO_2 emissions in the top ten emitter countries. The study concludes that, in the short run, EPU is responsible for a reduction in the levels of CO_2 emissions. Recently, Yu et al. (2021) also report that EPU leads to higher levels of CO_2 emissions in China. Conversely, Adedoyin and Zakari (2020) examine the impact of EPU on CO_2 emissions in the UK and report that EPU impedes CO_2 emissions in the short run. On the contrary, the study finds that EPU upsurges CO_2 emissions in the long run. Similarly, Syed and Bouri (2021) employ the bootstrap ARDL approach and conclude that EPU plunges CO_2 emissions in the long run. Syed and Bouri (2020) argue that EPU harms both GDP and energy consumption. As a result, CO_2 emissions do mitigate in the long run. Further, On the other hand, EPU contributes to strong CO_2 emissions in the long run. In addition to this, Chen et al. (2021)

documented that EPU impedes CO_2 emissions in the case of both developed and developing countries. Next, Abbasi and Adedoyin (2021) employ dynamic ARDL methodology to explore the effect of economic growth, energy, and EPU on CO_2 emissions. The findings of the study note that EPU does not affect CO_2 emissions in China, whereas energy and GDP escalate the CO_2 emissions.

Regarding the literature on the relationship between GPR and CO_2 emissions, Adams et al. (2020) investigate whether GPR and EPU affect CO_2 emissions in top resource-rich economies. The findings reveal that EPU escalates CO_2 emissions, while GPR plunges emissions. Recently, Anser et al. (2021b) employ an AMG estimator to investigate the long-run impact of GPR on CO_2 emissions. The results describe that GPR plunges renewable energy, R&D, and innovation. As a result, there has been a rise in the levels of CO_2 emissions. Further, Zhao et al. (2021) conclude that there exists an asymmetric impact of GPR on CO_2 emissions in BRICS countries.

Table 1: Literature summary

Study	**Variables**	**Methodology**	**Findings**
Jiang et al. (2019)	EPU and CO_2	Granger causality	EPU causes carbon emissions
Danish et al. (2020)	EPU, GDP, energy efficiency, and CO_2	Dynamic ARDL	EPU increases CO_2
Pirgaip and Dinçergök (2020)	EPU, GDP, energy, and CO_2	Panel causality test	EPU causes carbon emissions
Wang et al. (2020)	EPU, GDP, energy,	ARDL approach	EPU increases CO_2

	and CO_2		
Anser et al. (2021a)	EPU, GDP, population, energy, and CO_2	Panel ARDL	EPU increases CO_2 in the long-run
Yu et al. (2021)	Provincial-EPU and CO_2	Fixed effects model	EPU increases CO_2
Adedoyin and Zakari (2020)	EPU, GDP, energy, and CO_2	ARDL	EPU increases CO_2 in the long-run
Syed and Bouri (2021)	EPU, industrial production, renewable energy, and CO_2	Bootstrap ARDL	EPU decreases CO_2 in the long-run
Chen et al. (2021)	EPU, GDP, and CO_2	Fixed- and Random effects models	EPU decreases CO_2
Abbasi and Adedoyin (2021)	EPU, GDP, energy, and CO_2	Dynamic ARDL	EPU does not affect CO_2
Adams et al. (2020)	EPU, GPR, GDP, and CO_2	PMG-ARDL	EPU escalates CO_2, while GPR plunges it.
Anser et al. (2021b)	GPR, GDP, energy, and CO_2	AMG estimator	GPR increases CO_2
Zhao et al. (2021)	GPR, GDP, and CO_2	NARDL	GPR exerts asymmetric impacts on CO_2

2.2 Determinants of CO_2 emissions

There exist several studies that explore the determinants of CO_2 emissions employing a panel quantile regression approach. For instance, Salman et al. (2019) investigate the impact of imports, exports, energy intensity, and technology on CO_2 emissions for ASEAN-7 countries using a panel quantile regression approach. The study reports that exports and energy intensity escalates CO_2 emissions at several quantiles, whereas imports and technological advancement plunges the carbon emissions. Also, the study validates the environmental Kuznets curve (EKC) hypothesis for the ASEAN-7 economies. The study of Zhu et al. (2016) examines the effect of FDI, economic growth, and energy consumption on CO_2 emissions for ASEAN-5 economies. The findings reveal that Halo Effect Hypothesis exists for high emissions countries, whereas there is no association between FDI and CO_2 emissions for low emissions countries. Further, energy consumption and GDP also have heterogeneous impacts on CO_2 emissions across different quantiles. Moreover, the study notes that the EKC hypothesis does not exist within ASEAN-5 economies.

According to Zhang et al. (2016), who probe the impact of corruption and economic growth on CO_2 emissions for the Asia-Pacific Economic Cooperation region, heterogeneous impacts of corruption and GDP exist. The impact of corruption on CO_2 emissions is negative for lower quantiles, whereas there is no association between corruption and CO_2 emissions in higher quantiles. Additionally, the direct and indirect effects of corruption on CO_2 emissions are also heterogeneous across quantiles. Using provincial-level data, Xu and Lin (2016) investigate the effect of GDP, urbanization, industrialization, and energy intensity on CO_2 emissions for China. The findings expound that the impact of economic growth, on CO_2 emissions, is profound at higher quantiles, whereas there exists a meagre relationship between GDP and CO_2 emissions at lower quantiles. Also, the positive impact of urbanization, on CO_2 emissions, increases from lower to higher quantiles. Besides, the impact of industrialization plunges from higher quantiles to lower quantiles.

In addition, Zheng et al. (2019) ascertain the heterogeneous impact of GDP, urbanization, industrialization, and population on CO_2 emissions for selected Chinese cities. The authors explain that the positive impact of GDP on CO_2 emissions rises from lower quantile to higher quantile, whereas the positive impact of urbanization and industrialization plunges while moving from lower to higher quantile. Besides, the negative relationship between population and CO_2 emissions increases while moving from higher to lower quantiles. Nwaka et al. (2020) analyze the determinants of CO_2 emissions in selected West African countries. The results of their study describe that EKC does not exist for the selected countries. Moreover, there exists a positive impact of the agriculture sector on CO_2 emissions across all percentiles, whereas the impact of renewable energy on CO_2 emissions is negative in all quantiles. Additionally, there is a positive impact of trade on CO_2 emissions across all quantiles. Using panel quantile regression, Chou et al. (2019) documented that democracy escalates energy efficiency, and reduces the level of carbon emissions in selected countries of South America. Next, Alola et al. (2020) examine the impact of economic growth, energy consumption, urbanization, and tourism on carbon emissions, using panel quantile regression, for selected OECD countries. The findings of the study conclude that urbanization, tourism, and economic growth upsurge CO_2 emissions in upper (higher) quantiles.

Likewise, Akram et al. (2020) explore the environmental impact of energy consumption within the framework of the environmental Kuznets curve for developing countries while controlling the role of renewable energy, nuclear energy, and urbanization. The study confirms the validity of the environmental Kuznets curve and finds that energy efficiency mitigates carbon emissions. Moreover, the results of the study reveal that renewable and nuclear energy impedes carbon dioxide emissions. Next, Luo et al. (2020) examine the convergence of carbon emission coupled with its determinants for selected provinces of China. The study expounds that there exists convergence in CO_2 emissions in China. Moreover, inward FDI plunges the emissions across different quantiles, whereas outward FDI escalates the emissions. The study also validates the existence of the environmental Kuznets curve hypothesis. The study of Liu et al. (2019) investigates the nexus between income inequality and CO_2 emissions across states of the USA using panel quantile regression. The results declare that inequality improves the environmental quality, especially in high emissions states. Likewise, using panel quantile regression, Chen et al. (2020) explore the effect of income inequality on carbon emissions in both developed and developing countries. The study notes that income inequality escalates emissions in developing countries, whereas income inequality has a meagre impact on the level of emissions in developed countries. Cheng et al. (2021) investigate whether technological innovation affects carbon emissions in OECD countries. The findings from the panel quantile regression approach reveal that technological innovation impedes the emissions, however, the impact/ magnitude is heterogeneous across quantiles. Similarly, Yu et al. (2020) examine the effect of renewable energy on carbon emissions in China. The findings expound that renewable energy has a profound negative impact on CO_2 in high and low emission regions of China.

Recently, a few studies expound several new drivers of CO_2 emissions, such that, Qin et al. (2021) highlight that green innovations, composite risk, and environmental policy control environmental degradation. Similarly, Su et al. (2021) explore the political risk-environment nexus using advanced econometric methods. The authors documented that improved political scenario helps to achieve a clean environment. Similarly, Alola et al. (2021) pointed out that economic growth and technological innovation lead to sustainable development. Further, Usman et al. (2021) document that ICT has an asymmetric impact on carbon emissions in the case of selected Asian economics. Likewise, Shan et al. (2021) noted that institutional quality and energy prices have detrimental impacts on levels of emissions in the case of the top 7 OECD countries.

Table 2: Literature summary on CO_2 emissions' determinants

Study	Independent variables	Country/region	Findings
Salman et al. (2019)	Imports, exports, energy, technological advances	ASEAN-7	Exports and energy increase carbon emissions, while imports and technological progress plummets emissions.
Zhu et al. (2016)	FDI, economic growth, energy consumption	ASEAN-5	Economic growth and population size have a negative effect on CO_2 emissions in high-emissions countries.
Zhang et al. (2016)	Energy consumption, corruption, democratic accountability, per capita GDP	APEC countries	Corruption has a negative direct effect and a positive indirect effect on CO_2 emissions.

Xu and Lin (2016)	GDP, urbanization, industrialization, energy intensity	China	Economic growth plays a dominant role in the growth of CO_2 emissions.
Zheng et al. (2019)	GDP, urbanization, industrialization, population	China	The positive impact of GDP, urbanization and industrialization on CO_2 emissions rises but is inconsistent between population and CO_2 emissions.
Nwaka et al. (2020)	Agricultural value-added, renewable energy consumption, industry value-added, economic growth	ECOWAS region	Agriculture induced CO_2 emissions may emanate from cultivation and biomass use.
Chou et al. (2019)	Labor, economic output, capital input	26 South American countries	Democracy has an important impact on the reduction of national CO_2 emissions and brings a positive influence on energy efficiency.
Alola et al. (2020)	Real income per capita, international tourism	31 OECD countries	Urbanization, tourism, and economic growth upsurge

	arrivals, urbanization, energy consumption		CO_2 emissions in higher quantiles.
Akram et al. (2020)	Energy efficiency, per capita GDP, the square of per capita GDP, renewable energy, nuclear energy, urbanization	66 developing countries	Energy efficiency has heterogeneous effects and a robust negative effect on carbon emissions.
Luo et al. (2020)	Population, GRP per capita, patent application, urbanization, IFDI, OFDI	China	Outward foreign direct investment had negative effects on CO_2 emissions in China.
Liu et al. (2019)	Energy consumption, industry structure, per capita GDP	US	Higher-income inequality increases US carbon emissions in the short term, whereas it promotes carbon reduction in the long term.
Chen et al. (2020)	GDP per capita, energy consumption, FDI to GDP ratio, trade to GDP ratio,	17 G20 countries	In developing countries, inequality has a detrimental effect on CO_2 emissions another side

	urbanization, population density		most developed countries, income inequality hardly affects CO_2 emissions.
Cheng et al. (2021)	GDP per capita, investment, renewable energy supply, development of patent technologies, export trade values	35 OECD countries	Technological innovation indirectly affects emissions by offsetting the positive impact of economic growth.
Yu et al. (2020)	Renewable energy generation, energy intensity, energy structure, industrial structure, GDP per capita, urbanization rate	China	China's renewable energy development has a limited effect on its carbon reduction but it becomes more and more obvious with time.

2.3. Theoretical Framework

This section theoretically describes that how EPU and GPR affect CO_2 emissions. According to Jiang et al. (2019), there are two channels/ effects that link EPU with CO_2 emissions: (1) direct policy adjustment effect; (2) indirect economic demand effect. The direct policy adjustment effect expounds that increase in EPU averts the focus of policymakers from environmental quality to economic stability. As a result, CO_2 emissions escalate in the economy.

Parallel to this, the indirect economic demand effect shows that EPU affects the decision-making and economic behaviour of consumers and producers, which in turn raises the levels of energy consumption. As a result, CO_2 emissions surge in the country.

Similarly, Wang et al. (2020) describe that EPU alters CO_2 emissions through consumption effect and investment effect. The consumption effect expounds that EPU impedes the use of energy (i.e., non-renewable energy) and carbon-emitting consumers' goods. As a result, CO_2 emissions will be decreased. On the contrary, the investment effect notes that EPU mitigates the investment in R&D, technological advancement, and innovation. Hence, CO_2 emissions will have surged.

Likewise, Yu et al. (2021) also developed three channels that link economic policies uncertainty with CO_2 emissions. These three channels comprise the innovations channel; share of fossil fuel energy channel; and energy intensity channel. Innovation channel shows that policy-related uncertainties lead to fewer innovations, thus, the level of CO_2 emissions will be increased. Next, the share of fossil fuel channel describes that EPU surges the share of non-renewable energy in the energy mix, which leads to higher levels of CO_2 emissions. Moreover, the energy intensity channel explains that EPU upsurges the energy intensity, which on the contrary, intensifies levels of CO_2 emissions.

Parallel to this, Anser et al. (2021c) put forward escalating effect and mitigating effects of GPR, which link GPR with environmental degradation. According to escalating effect, GPR impedes R&D, technological advancement, and innovation. As a result of this, CO_2 emissions will be escalated. Conversely, mitigating effect reports that GPR plunges economic growth and energy consumption, hence, CO_2 emissions will be reduced.

3. Data, Model and methodology

3.1 Model

To evaluate the impact of human activities on environmental degradation, IPAT (I (influence) = P (population), A (affluence), T (technology)) framework has extensively been applied in empirical studies related to environmental economics. However, it has been noticed that IPAT contains a few limitations: (1) due to its mathematical form, application of hypothesis testing is not conceivable; (2) fixed proportionality through all independent variables is assumed in IPAT framework, which is invalid; (3) IPAT model does not discriminate the relative imperativeness of every independent variable (Anser et al., 2021a; York et al., 2003). To cover these aforementioned demerits, Dietz and Rosa (1994) develop stochastic impacts by regression on population, affluence, and technology (STIRPAT) framework. The STIRPAT model in its general form is presented as follows:

$$I_{it} = \emptyset P_{it}^{\beta 1} A_{it}^{\beta 2} T_{it}^{\beta 3} \varepsilon_{it} \tag{1}$$

In Eq. (1), I denotes influence (proxied by carbon dioxide emissions), P represents the population, A is affluence (proxied by GDP per capita), and T is technology (represented by energy consumption). Further, ∅ denotes intercept, i is a cross-section (country in this study), t represents time, and ε is the error term. Also, β_i (i=1,2,3) is coefficient. We incorporate economic policy uncertainty and geopolitical risk in the STIRPAT model for this analysis.

$$I_{it} = \emptyset P_{it}^{\beta 1} A_{it}^{\beta 2} T_{it}^{\beta 3} EPU_{it}^{\beta 4} GPR_{it}^{\beta 5} \varepsilon_{it} \tag{2}$$

In Eq. (2), EPU represents economic policy uncertainty and GPR is geopolitical risk. Also, β_4 and β_5 are the coefficients of EPU and GPR, respectively. After taking the logarithm of all variables, and substituting *A*, *P*, *T*, and *I* for their proxies, the final equation (i.e., empirical model of this study) is reported in Eq. (3):

$$LCO_{2,it} = \emptyset_{it} + \beta_1 LURB_{it} + \beta_2 LGDP_{it} + \beta_3 LNRE_{it} + \beta_4 LREN_{it} + \beta_5 LEPU_{it} + \beta_6 LGPR_{it} + \varepsilon_{it} \quad (3)$$

Where LCO_2 represents the log of CO_2 emissions (proxy of influence), LURB is the log of urbanization (proxy of the population), LGDP denotes log of GDP per capita (proxy of affluence), LNRE is the log of non-renewable energy consumption, LREN is the log of renewable energy, LEPU denotes log of economic policy uncertainty (EPU), and LGPR represents the log of geopolitical risk (GPR). It is worth mentioning that renewable and non-renewable energy consumption is used as a proxy of technology *(T)*. Further, $\emptyset$ is intercept, *i* is a cross-section, *t* denotes period, and ε is the error term. In addition, β_i (i=1, 2,..., 6) is the coefficient of the STIRPAT model.

3.2 Methodology

It is known that OLS regression renders an unbiased estimator with a minimum variance if: (1) error term of OLS regression has zero mean, and it has identical distribution (*i, i, d*); and (2) error term follows the normal distribution. According to De Silva et al. (2016), these aforementioned assumptions are not realistically provided the nature of economic variables in real life. To cover the demerits of OLS regression, Koenker and Bassett (1978) presented quantile regression. There exists several advantages of quantile regression: (1) the quartile regression does not possess any assumption related to the occurrence of moment function (Zhu et al., 2016); (2) quantile regression renders relatively accurate and robust results even in the case of outliers and fat tail distribution (Bera et al., 2016); (3) it does not develop any assumption regarding the distribution (Sherwood and Wang, 2016). These aforementioned properties of quantile regression prompt this study to employ this methodology.

$$Q_{yi}\,(\emptyset|x_i) = x_i^{/}\alpha_{\emptyset} \tag{4}$$

Eq. (4) demonstrates the conditional quantile Y_i in a given x_i, however, $\emptyset$ denotes the quantile. While using quantile regression methodology in panel data, unobserved heterogeneity is taken into account which prompts to employ panel quantile regression model with a fixed effect. This model enables us to control unobserved individual heterogeneity. The panel quantile regression model with fixed effect is mentioned as follows.

$$Q_{yit}\,(\emptyset_k|\varphi_i, x_{it}) = \varphi_i + x_{it}^{/}\alpha(\emptyset_k) \tag{5}$$

In Eq. (5), φ_i captures the fixed effect that also brings the incidental parameter problem (Lancaster, 2000). With fixed time-series observations for each cross-sectional unit, the estimator becomes inconsistent when the cross-sectional unit approaches infinity (Galvao and Kato, 2016). Thus, we can't use conventional linear approaches in the panel quantile regression model.

Koenker (2004) develops an approach that is known as the shrinkage method, to solve the aforementioned problem of panel quantile regression. This method introduces a penalty term to eliminate the unobserved fixed effects. The parameters of the model are estimated as follows.

$$(\hat{\alpha}(\emptyset_k,\eta),\{\varphi_i\,(\eta)\}^{N}_{i=1}) = \arg\min \sum_k^K \sum_t^T \sum_i^N \Omega_k\, \rho_{\emptyset k}(\, y_{it} - \varphi_i - x_{it}^{/}\alpha(\emptyset_k)) + \eta \sum_i^N |\,\varphi_i|, \tag{6}$$

In Eq. (6), i and t represent country and year, respectively. Further, k represents the quantile however $\rho_{\emptyset k}$ shows the quantile loss functions. Moreover, Ω_k denotes the given weight that is assigned to k-th quantile. Also, Ω_k captures the contribution of different quantiles. Similar to Lamarche (2011), we also set $\Omega_k = 1/k$. In addition, η is tunning term/parameter that is used to plunge the individual effect to zero for better estimation of slope coefficients in the model. We also set the value of η = 1 as many studies, for instance, Zhu et al. (2018), set the value of η =1.

3.3 Data

The present study aims to evaluate the impact of economic policy uncertainty and geopolitical risk on CO_2 emissions in BRICST (Brazil, Russia, India, China, South Africa, and Turkey) countries. We make use of panel data spanning 1990-2015 on annual frequency. The dependent variable of the current study is CO_2 emissions (measured in metric tons per capita), whereas key independent variables/ regressors are economic policy uncertainty and geopolitical risk. The world uncertainty index, which is calculated based on the frequency of articles containing the "uncertainty" related words in Economic Intelligence Unit reports, is used as a proxy for economic policy uncertainty. Recently, several studies employ this world uncertainty index as a proxy to measure economic policy uncertainty (see, for example, Adams et al., 2020; Wang et al., 2020; Anser et al., 2021a). On the other hand, the geopolitical risk index, which is also calculated based on the frequency of articles containing "geopolitics" related words in a leading newspaper, is used as a proxy of geopolitical risk. Recently, many researchers use this proxy such as Adams et al. (2020) and Anser et al. (2021b). The data on both variables (i.e., world uncertainty index and geopolitical risk index) are gathered from *policyuncertainty.com*. Also, GDP per capita (measured in constant $2010), urbanization (measured as a percentage of urban population), non-renewable energy (measured as oil equivalent per capita), and renewable energy (measured as a share of renewables in total energy) are the control variables. Data on these aforementioned variables and CO_2 emissions are collected from WDI (World Development Indicators) database. The description of the data is reported in table 3.

Table 3: Summary of the data

Variable	Symbol	Measurement Scale	Source
Carbon dioxide emissions	LCO_2	Metric ton per capita	WDI
Economic policy uncertainty	LEPU	World uncertainty index which is based on the frequency of articles containing “uncertainty” related words in EIU reports	Policyuncertainty.com
Geopolitical risk	LGPR	Geopolitical risk index which is based on the frequency of articles containing “geopolitics” related words in the newspaper	Policyuncertainty.com
Non-renewable energy	LNRE	Oil equivalent per capita	WDI
Renewable energy	LREN	Share of renewables in the energy mix	WDI
Urbanization	LURB	Percentage of urban population	WDI
GDP per capita	LGDP	Constant $2010	WDI

Note: All variables are converted in logarithmic form. Further, WDI is World Development Indicators, while EIU is Economic Intelligence Unit.

The descriptive statistics of the considered variables are reported in Table 4. As can be seen from Table 4, the mean value of LURB is the highest, whereas it is the lowest for LEPU. Similarly, the standard deviation of LURB is also the highest, while it is the lowest for LGPR. The values of skewness elaborate that all variables have either positive or negative skewness except for LNRE, which is neither positively nor negatively skewed. In the same way, kurtosis expounds that a few considered variables (e.g., LEPU) contain heavy/ fat tail. In addition, the Jarque-Bera test reveals that all considered variables of this study contain non-normal distribution because the null hypothesis of normal distribution could be rejected for all variables in this study.

Table 4: Descriptive statistics

	LCO2	**LGDP**	**LREN**	**LNRE**	**LURB**	**LGPR**	**LEPU**
Mean	0.57	3.66	1.28	3.16	8.07	3.08	-0.73
St. dev.	0.37	0.40	0.38	0.32	0.45	0.09	0.40
Skewness	-0.05	-0.97	-0.77	0.00	-0.03	0.57	-1.33
Kurtosis	1.87	2.48	2.55	2.18	1.84	3.04	6.81
Jarque-bera	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.02)**	(0.00)***

*Note: (.) denotes probability value. Further, *, **, *** represent level of sig. at 10%, 5%, and 1%, respectively.*

Apart from the Jarque-Bera test, we also employ a Q-Q plot to graphically show the distribution of the variables. In the Q-Q plot, the linear diagonal blue line shows the normal distribution, while the dotted line describes the deviation from the normal distribution. Fig. 4-10 elaborate that all selected variables have non-normal distribution.

[Insert figure 4-10 here]

Moreover, the pairwise correlation between all selected variables of this study is reported in Table 5. As can be seen from Table 5, the correlation of LCO_2 with LNRE and LURB is negative, while it is positive for all other variables. Additionally, correlation is the highest between LCO_2 and LNRE, which is 0.96. Also, it is the lowest between LCO_2 and LEPU, which is 0.08.

Table 5: Correlation

	LCO2	**LGDP**	**LREN**	**LNRE**	**LURB**	**LGPR**	**LEPU**
LCO2	1.00						
LGDP	0.58	1.00					
LREN	-0.88	-0.48	1.00				
LNRE	0.96	0.70	-0.87	1.00			
LURB	-0.43	-0.57	0.26	-0.43	1.00		
LGPR	0.14	0.11	-0.14	0.12	-0.21	1.00	
LEPU	0.08	0.43	-0.09	0.17	-0.45	0.07	1.00

4. Results and Discussions

This section presents the findings in detail. We follow the five-step procedure to report the findings in a plausible form.

In step-1, we probe the cross-sectional dependence (CD) using several tests (e.g., Pesaran CD test, Friedman CD test, and Frees CD test), and slope heterogeneity test by Pesaran and Yagamata (2008). In the panel dataset, CD refers to the spillover effect of a shock from one cross-section to another, and the proper scrutiny of CD is indispensable because its presence could lead to spurious findings (Pesaran, 2007). Parallel to this, ignoring slope heterogeneity may also lead to spurious outcomes. The findings from the CD tests and slope heterogeneity test are presented in table 6.

Table 6: Cross-sectional dependence tests

	CD test			**Slope heterogeneity test**	
	Pesaran CD test	**Friedman CD test**	**Frees CD test**	Δ	$\Delta_{Adj.}$
LCO2=f(LGDP, LREN, LNRE, LGPR, LEPU, LURB)	(0.02)**	(0.00)***	(0.02)**	112.32***	131.01***

*Note: (.) represents p-value. *, **, *** denote significance level at 10%, 5%, and 1%, respectively.*

As can be seen from Table 6, the null hypothesis of no cross-sectional dependence could be rejected from all tests. Thus, it could be implied that there exists CD. Similarly, the findings from the slope heterogeneity test document that there exists slope heterogeneity since we could reject the null hypothesis of no slope heterogeneity.

In step-2, we probe the unit root/ stationary property of the variables. The application of the unit root test is imperative for appropriate estimation/regression methodology, and reliable results. There are several panel data unit root tests in the literature; however, most of them (e.g., LLC unit root test and IPS unit root test, etc.) do not cover the issue of CD. Hence, these tests may lead to unreliable findings. On the contrary, the CIPS unit root test and CADF unit root test cover both CD and heterogeneity, therefore, these tests outperforms other first-generation panel unit root tests (i.e., LLC unit root test and IPS unit root test, etc.). Given the advantages of CIPS and CADF unit root tests, we also apply these tests in this study. The findings from CIPS and CADF unit root are reported in table 7, and it can be seen from table 7 that we could not reject the null hypothesis of there is a unit root at I (0) or level form. On the contrary, we could reject the null hypothesis at I (1) for all variables.

Table 7: Unit root tests

	CIPS test		**CADF test**	
	Level	**1st difference**	**Level**	**1st difference**
LCO2	-2.01	-2.87	-2.13	-3.32
LGDP	-1.99	-2.90	-1.93	-3.78
LREN	-2.03	-3.46	-2.07	-2.64
LNRE	-2.32	-3.21	-2.48	-4.18
LGPR	-1.29	-2.65	-1.46	-3.36
LEPU	-2.38	-4.64	-1.39	-2.59

Note: Critical value of CIPS at 1% is -2.51, whereas the critical value of CADF at 1% is -2.57

In step-3, we investigate whether there is a long-run (co-integration) relationship among the selected variables of the study. In the prior literature, there are many panel co-integration methods. However, conventional panel co-integration methodologies (e.g., Kao test and Pedroni test, etc.) do not incorporate the issue of CD and heterogeneity, which could render spurious results. To overcome the demerits of the first-generation (conventional) co-integration methodologies, Westerlund (2007) test is developed which covers the problem of CD and heterogeneity. The results from Westerlund (2007) test are presented in table 8. Table 8 elaborates that the null hypothesis of no co-integration could be rejected for all four test statistics. Thus, it could be stated that there exists a long-run relationship among the selected variables of the study.

Table 8: Westerlund (2007) test

Statistic	**Value**	**p-value**
G_t	-11.01	0.00***
G_a	-8.32	0.00***
P_t	-10.83	0.00***
P_a	-4.97	0.00***

*Note: *** indicates the level of significance at 1%.*

In step-4, this study employs an augmented mean group (AMG) estimator and the Common Correlated Effects Mean Group (CCEMG) estimator for long-run elasticity. The motivation behind applying AMG and CCEMG is twofold: (1) these aforementioned methodologies cover both the CD and heterogeneity issue (Pesaran, 2006; Adedoyin et al., 2021); (2) there is no need to examine the unit root and co-integration before applying these methods (Anser et al., 2021b). Table 9 presents the findings from AMG and CCEMG estimators.

Table 9: Findings from AMG and CCEMG estimator

Variable	AMG estimator	CCEMG estimator
LGDP	0.13	0.17
LREN	-0.39***	-0.48***
LNRE	0.87***	0.81***
LURB	1.02	-2.44***
LEPU	-0.37	0.00
LGPR	-0.62	-0.05***

*Note: *** indicates the level of significance at 1%.*

Results from the AMG estimator reveal that all variables are statistically insignificant except LREN and LNRE, which are statically significant at 1%. The value of LREN is –0.39, which implies that a 1% increase in renewable energy plunges the CO_2 emissions by 0.39%. On the other hand, the value of LERE is 0.87, indicating that a 0.87% increase in CO_2 emissions is fostered by a 1% increase in non-renewable energy. By implication of the result, renewable energy share among the panel countries (Brazil, Russia, India, China, South Africa, and Turkey) importantly drives the environmental sustainability agenda while traditional energy such as fossil fuel remained a setback to such aspired agenda. The respective evidence of the negative and positive impact of renewable and non-renewable on environmental degradation has been widely illustrated in the literature (Bekun et al., 2019; Saint Akadiri et al., 2019; Usman et al., 2020).

On the contrary, the findings from the CCEMG estimator highlight that all variables are statistically significant except LGDP and LEPU, which are statistically insignificant. Regarding LREN, the value of the coefficient is -0.48. This indicates that a 1% increase in renewable energy impedes CO_2 emissions by 0.48%. The coefficient of LNRE is 0.81, which implies that a 0.81% surge in CO_2 emissions is fostered by a 1% rise in non-renewable energy consumption. On the contrary, the value of LURB is -2.44, highlighting that a 1% increase in urbanization plunges CO_2 emissions by 2.44%. In the literature, there have been divergent and inconclusive perspectives on the role of urbanization as a driver of environmental sustainability. For instance, while Onifade et al (2021) affirm the desirable impact of urbanization on environmental quality among the Organization of Petroleum Exporting Countries (OPEC), the studies of Asongu et al (2020) for Africa and Koyuncu et al (2021) for Turkey established a positive relationship between urbanization and environmental degradation. Moreover, the coefficient of LGPR is -0.05, indicating that a 0.05% decrease in CO_2 emissions is fostered by a 1% rise in geopolitical risk. Given that Olanipekun and Alola (2020) hints that geopolitical risk hampers oil production in the Persian Gulf region, the implication is geopolitical risk potentially mitigates environmental damage as supported in the current study. It is worth noting that AMG and CCEMG estimator is mean based regression methodologies, and we find contrasting results from these aforementioned methodologies.

In step-5, we report the results from panel quantile regression which expectedly addresses the drawbacks of the mean-based approach. Additionally, we present findings from the fixed-effects model to facilitate comparison. In table 10, the results from the fixed-effects model expound that all variables are statistically significant except LEPU, which is statistically insignificant. Further, it could be concluded that renewable energy plunges LCO_2 emissions, whereas the LGDP per capita, non-renewable energy, geopolitical risk, and urbanization contribute to high levels of CO_2 emissions.

Regarding the findings from panel quantile regression, we present the results at 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, and 90th quantiles. There exists a positive impact of LGDP (log of GDP per capita) on LCO_2 (log of CO_2 emissions per capita) across all quantiles, however, the strength of the relationship is heterogeneous. Thus, we note that LGDP escalates LCO_2 in high-, middle-, and lower-emission countries. It is worth noting that the impact of LGDP on emissions is relatively strong at extreme quantiles (i.e., 10th and 90th), confirming that the impact of LGDP is profound on countries with either higher or lower levels of emissions. Our finding is somehow backed by the studies of Zheng et al. (2019). Further, there is the negative impact of renewable energy (LREN) on CO_2 emissions (LCO_2) at all quantiles. Additionally, the relationship is relatively strong at higher and lower quantiles (i.e., 10th, 20th, 80th, 90th). This implies that renewable energy is a tool to impede CO_2 emissions, especially in higher and lower emission countries. This depicts that higher emitter BRICST countries are on the right path of achieving carbon neutrality through the use of renewables. This outcome is backed by the study of Yu et al. (2020). Next, we conclude that LNRE (non-renewable energy) surges CO_2 emissions at all quantiles. Although the strength of this relationship is heterogeneous at all quantiles yet there is a profound impact of LNRE on CO_2 emissions at 10th and 20th quantiles. It is worth reporting that nonrenewables consist of fossil fuels, which possess high carbon proportions. As a result, carbon emissions will be increased in the BRICST countries. This conclusion is in line with the results of Zhu et al. (2016). The results of LURB (urbanization) are slightly different from other control variables. That is, there exists a negative relationship between LURB and CO_2 emissions at lower quantiles, whereas the impact of LURB on CO_2 emissions is positive at middle and higher quantiles. Hence, we note that LURB mitigates CO_2 emissions in lower emission countries, while LURB leads to high CO_2 emissions in high emissions countries. It might be possible that in the low emitter countries, urbanization brings relatively better infrastructure, e.g., renewable energy-based technologies, etc. Moreover, urbanization may propel individuals to demand a healthy environment. On the contrary, in higher emission countries, urbanization can also increase the NREN, to meet the higher energy demand, and hence can contribute to emissions. These results are similar to the conclusion of Alola et al. (2020).

Concerning LEPU (economic policy uncertainty), there exists a negative effect of LEPU on CO_2 emissions at lower and middle quantiles. Whereas, LEPU escalates the LCO_2 at higher quantiles. Therefore, we report the heterogeneous impact of LEPU which is in contract with the positive relationship that has been largely revealed in the literature (Adedoyin & Zakari, 2020; Anser et al., 2021a; Syed & Bouri, 2021; Yu et al., 2021). At lower and middle quantiles (i.e., countries with relatively low emission levels), it could be reported that the strength of the consumption effect is higher than the other channels/effects. Hence, EPU plummets the use of non-renewable energy and pollution-intensive goods, thereby reducing CO_2 emissions is relatively low emitter countries. Conversely, in high emission countries (at high quantiles), the magnitude of the consumption effect is smaller than the other channels. This implies, EPU plummets the investment in renewable energy, increases the share of non-renewable energy in the energy mix, and escalates the energy intensity. As a result, the level of CO_2 emission surges in high carbon emitter countries (i.e., China and Russia). Notably, China and India are among the top emitters in the case of BRICST countries wherein economic uncertainty has also been upsurging over the years. Parallel to this, the level of emissions in these countries is also rising, inferring that uncertainty in economic policies also causes carbon emissions. On the contrary, Brazil and Turkey are among the lowest emitters in the case of BRICST countries wherein emissions have witnessed meagre growth over time. Also, uncertainty related to economic policy in these aforementioned countries has relatively been plunging, inferring that EPU may cause detrimental impacts on emissions.

Additionally, the effect of LGPRU on LCO_2 is positive at 10th, 20th, 30th, and 40th quantiles. While, there exists a negative effect of LGPR on LCO_2 at all other quantiles (1.e., 50th, 60th, 70th, 80th, and 90th). Moreover, the strength of the relationship plunges from the 10th to 40th quantile, and then it increases from 50th to 90th quantile. At 10th, 20th, 30th, and 40th quantile, escalating effect is dominant, implying that GPR discourages investment in R&D and renewable energy. As a result, carbon emission escalates in low emitter countries. These findings are in line with the conclusions of Anser et al. (2021b). On the other side, the strength of the mitigating effect is relatively high at 50th-90th quantiles. This indicates that GPR impedes economic growth and non-renewable energy consumption, thereby level of CO_2 emissions drop in high emitter countries. These findings are backed by the results of Adams et al (2020) and Anser et al. (2021c). These findings note that, in low emitters (i.e., Brazil and Turkey), LGPR is one of the critical drivers of emissions. On the contrary, in high emitter countries (i.e., China and India), LGPR curbs emissions.

Table 10: Results from fixed effect and panel quantile regression model

Variable	Fixed effects	Panel quantile regression								
		10^{th}	20^{th}	30^{th}	40^{th}	50^{th}	60^{th}	70^{th}	80^{th}	90^{th}
LGDP	0.410***	0.171***	0.040***	0.062***	0.102***	0.061***	0.045***	0.081***	0.041***	0.252***
LEPU	-0.001	-0.001***	-0.002***	-0.001***	-0.015***	-0.030***	-0.023***	0.037***	0.014***	0.018***
LGPR	0.038*	0.031***	0.019***	0.014***	0.003***	-0.001***	-0.013***	-0.017***	-0.018***	-0.035***
LREN	-0.241***	-0.191***	-0.206***	-0.113***	-0.153***	-0.191***	-0.152***	-0.163***	-0.212***	-0.228***
LNRE	0.851***	1.091***	0.969***	0.931***	0.893***	0.962***	0.953***	0.916***	0.954***	0.722***
LURB	1.401***	-0.269***	-0.092***	-0.291***	0.339***	0.096***	0.201***	0.453***	0.417***	0.257***

*Note: *, **, *** denote significance level at 10%, 5%, and 1%, respectively.*

Table 11: Summary of findings from panel quantile regression

Variable	Low quantiles	Middle quantiles	High quantiles
	10^{th}, 20^{th}, 30^{th}	40^{th}, 50^{th}, 60^{th}	70^{th}, 80^{th}, 90^{th}
LGDP	+	+	+
LEPU	-	-	+
LGPR	+	-	-
LREN	-	-	-
LNRE	+	+	+
LURB	-	+	+

Note: "+" denotes a statistically significant and positive relationship, whereas "-"shows a negative and statistically significant relationship. For this analysis we set λ=1.

In Table 11, we summarize the findings from panel quantile regression. As can be seen that LGDP and LNRE positively affect LCO_2 at all quantiles, while LREN adversely affects LCO_2 across all quantiles. Moreover, at lower quantiles, LURB plunges LCO_2, while it surges LCO_2 at middle and higher quantiles. Regarding LEPU, it adversely affects LCO_2 at lower and middle quantiles. However, LEPU escalates LCO_2 at higher quantiles. On the contrary, LGPR impedes LCO_2 at lower and middle quantiles, whereas it surges LCO_2 at higher quantiles.

Furthermore, we probe the robustness of findings by setting different values of λ (i.e., λ= 0.9 and λ=1.5). The results are almost similar to our aforementioned findings when λ=1. To save the space we just mention the summary of panel quantile models at λ= 0.9, and 1.5. Table 12 presents the results as follows:

Table 12: Robustness check

Variable	Low quantiles	Middle quantiles	High quantiles
	10th, 20th, 30th	40th, 50th, 60th	70th, 80th, 90th
	λ= 0.9		
LGDP	+	+	+
LEPU	-	-	+
LGPR	+	-	-
LREN	-	-	-
LNRE	+	+	+
LURB	-	+	+
	λ= 1.5		
LGDP	+	+	+
LEPU	-	-	+
LGPR	+	-	-
LREN	-	-	-
LNRE	+	+	+
LURB	-	+	+

Note: "+" denotes a statistically significant and positive relationship, whereas "-"shows a negative and statistically significant relationship. All coefficients are statistically significant either at a 1% or 5% level of significance.

5. Conclusion

In recent times, economic policy uncertainty and geopolitical risk have escalated exponentially, and these factors affect both the economy and the environment. Therefore, the objective of this study is to investigate whether economic policy uncertainty and geopolitical risk impede CO_2 emissions in BRICST countries. We employ second generation panel data methods, AMG and CCEMG estimator, and panel quantile regression model. We find that all variables are integrated at I (1), and there exists co-integration among considered variables of the study. Moreover, we note that economic policy uncertainty and geopolitical risk have a heterogeneous impact on CO_2 emissions across different quantiles. Economic policy uncertainty adversely affects CO_2 emissions at lower and middle quantiles, while it surges the CO_2 emissions at higher quantiles. On the contrary, geopolitical risk surges CO_2 emissions at lower quartiles, and it plunges CO_2 emissions at middle and higher quantiles. Further, GDP per capita, non-renewable energy, renewable energy, and urbanization also have a heterogeneous impact on CO_2 emissions in the conditional distribution of CO_2 emissions.

Based on the aforementioned findings, we deduce a few policy implications reported as follows:

(1) Since economic policy uncertainty impedes CO_2 emissions in low- and middle-emissions countries, any attempt to control uncertainty in economic policies will raise the level of CO_2 emissions. Therefore, policymakers should be well aware of the environmental impacts that EPU can exert.

(2) Policymakers should initiate the measures to increase technological advancement and innovations if they want to simultaneously mitigate both CO_2 emissions and economic policy uncertainty;

(3) We report that economic policy uncertainty surges CO_2 emissions at high-emissions countries, therefore, policymakers should control economic policy uncertainty to limit CO_2 emissions in those countries. In this regard, they should introduce anticipated economic policies. Also, the economic policies should be announced for next a few years to eliminate the uncertainty;

(4) Since external shocks (e.g., pandemics and economic crisis, etc.) contribute to EPU and hence emissions in high emitter countries, the policymakers need to devise plans to counter the environmental impacts of external shocks;

(5) Policymakers should control geopolitical risk in low- and middle-emissions countries since there exists a positive relationship between geopolitical risk and CO_2 emissions. For this purpose, governments should initiate peace programs, sign peace treaties, and take measures to control terrorism, wars, and geopolitical conflicts;

(6) In low and middle emissions countries, government officials should devise policies to control civil wars, impeachments, and religious & ethnic conflicts that boost geopolitical tensions and hence cause strong emissions;

(7) There is a need to initiate cultural exchange programs, international student scholarship programs, and multinational peace summits to bring people together that may limit the conflicts among nations, which, in turn, helps to control emissions;

(8) International organizations (e.g., United Nations, etc.) should play their role to shrink the geopolitical tensions, which, in turn, can control emissions;

(9) Since geopolitical risk plunges CO_2 emissions at high-emissions countries, policymakers should seek alternatives (e.g., renewable energy, R&D investment, and restrictions on

pollution-intensive goods, etc.) to simultaneously control both CO_2 emissions and geopolitical risk;

(10) There should be restrictions on imports of goods that consume non-renewable energy. Further, the share of renewable energy in total energy consumption should be escalated by rendering different incentives. For instance, there should be tax exemption on renewables imports. Next, investment in R&D related to renewable energy should also be encouraged;

(11) To encourage renewables, proper policies related to feed-in-tariff should be introduced.

Declarations

Acknowledgement: The authors acknowledge the participatory contribution of all respondents to this study.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Author Contributions: All authors strongly believe that they have made an equal and substantial contribution to prepare this manuscript. **Qasim Raza Syed**: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Software, Visualization, Roles/Writing - original draft, Writing - review & editing. **Roni Bhowmik**: Conceptualization, Data curation, Investigation, Project administration, Resources, Supervision, Visualization, Roles/Writing - original draft, Writing - review & editing. **Festus Fatai Adedoyin**: Conceptualization, Investigation, Methodology, Supervision, Validation, Writing - review & editing. **Andrew Adewale Alola**: Investigation, Methodology, Software, Supervision, Validation, Writing - review & editing. **Noreen Khalid**: Data curation, Formal analysis, Resources, Software, Roles/Writing - original draft.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing does not apply to this article.

Conflicts of Interest: The authors declare no conflict of interest.

Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Consent to Participate: Not applicable.

Consent for Publication: Not applicable.

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Appendix

Figure 4: Q-Q plot of CO_2 emissions

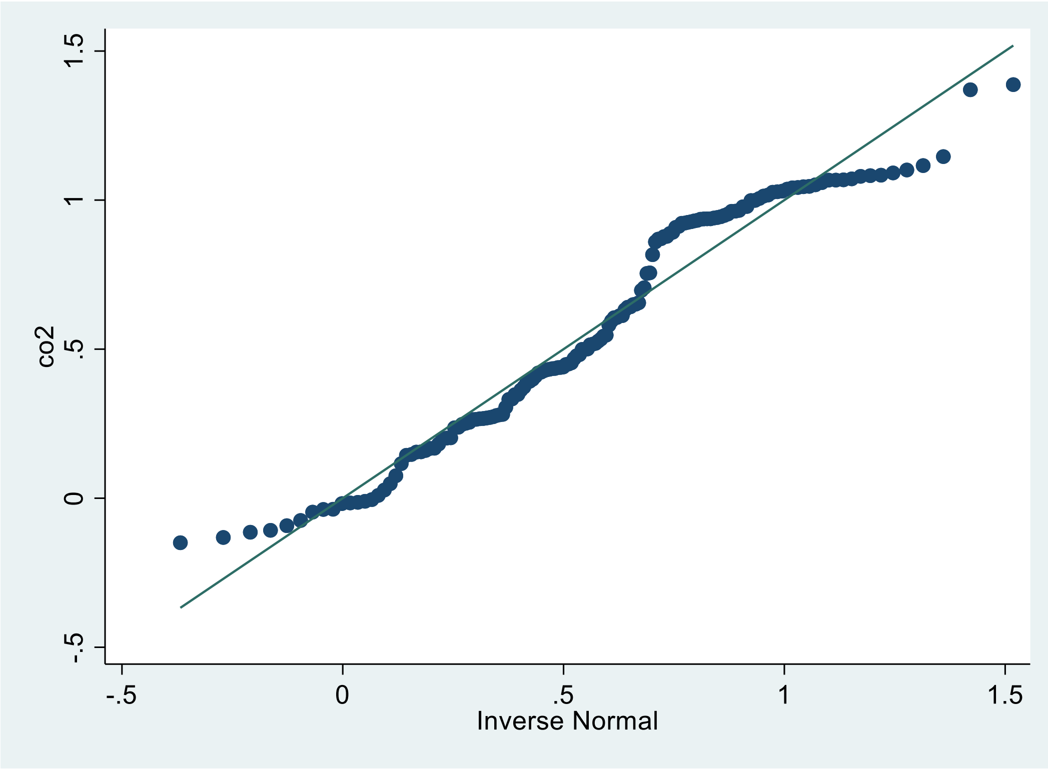

Figure 5: Q-Q plot of economic policy uncertainty

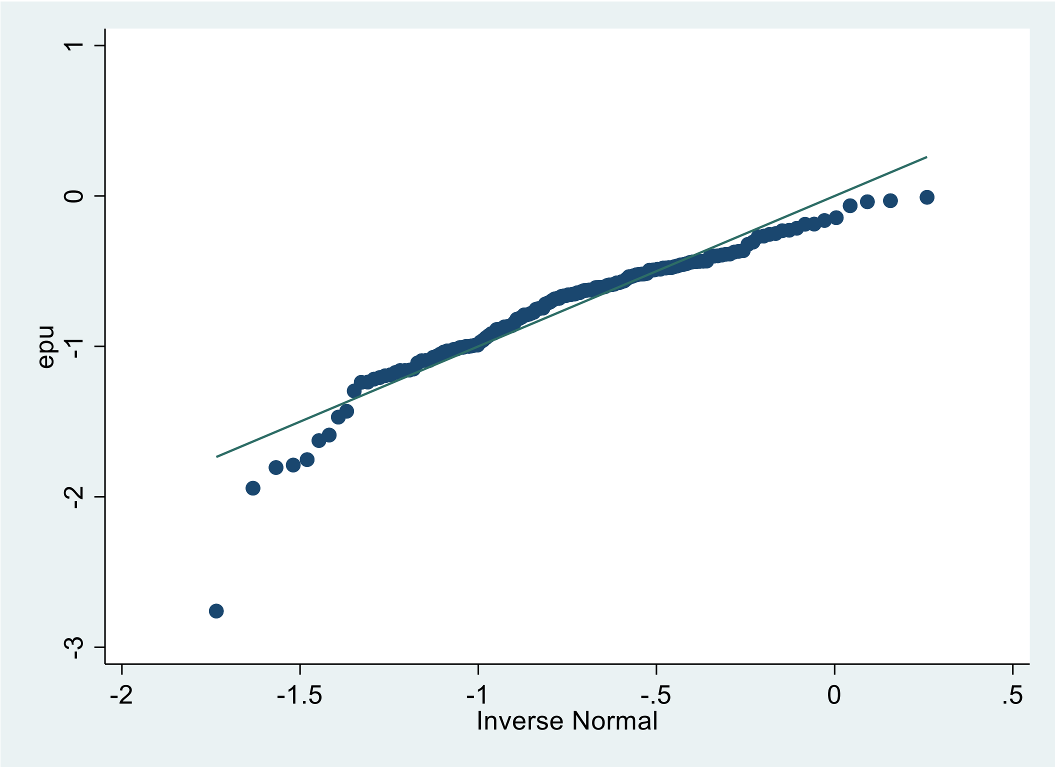

Figure 6: Q-Q plot of GDP per capita

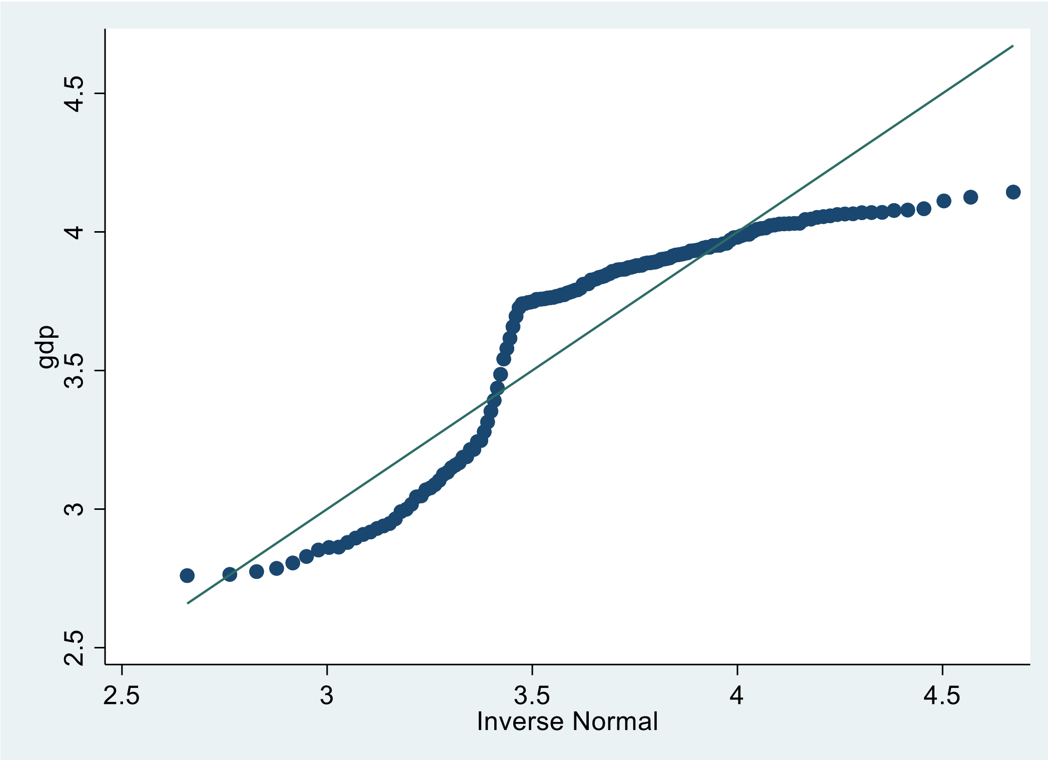

Figure 7: Q-Q plot of geopolitical risk

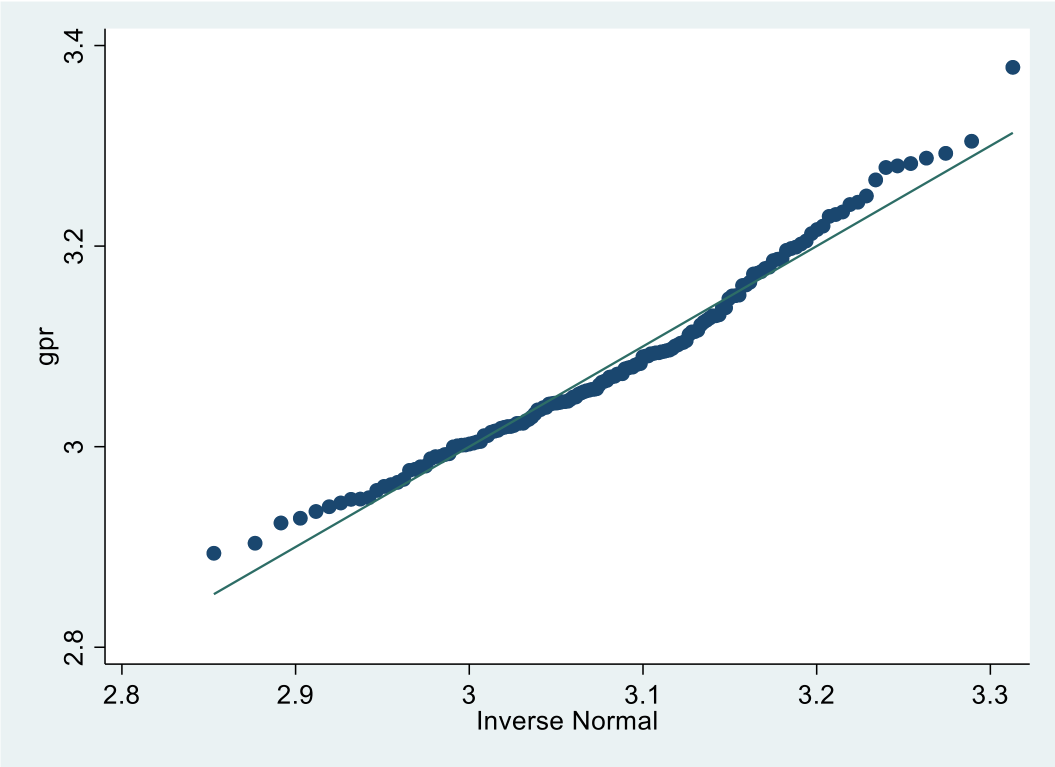

Figure 8: Q-Q plot of non-renewable energy

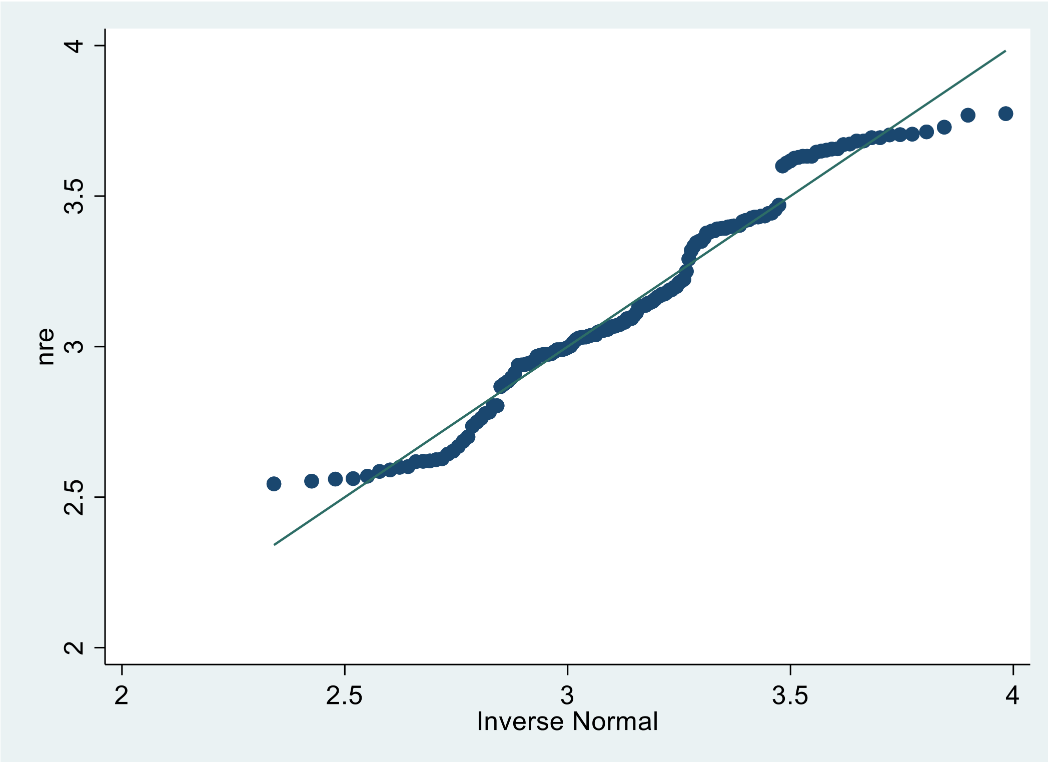

Figure 9: Q-Q plot of renewable energy

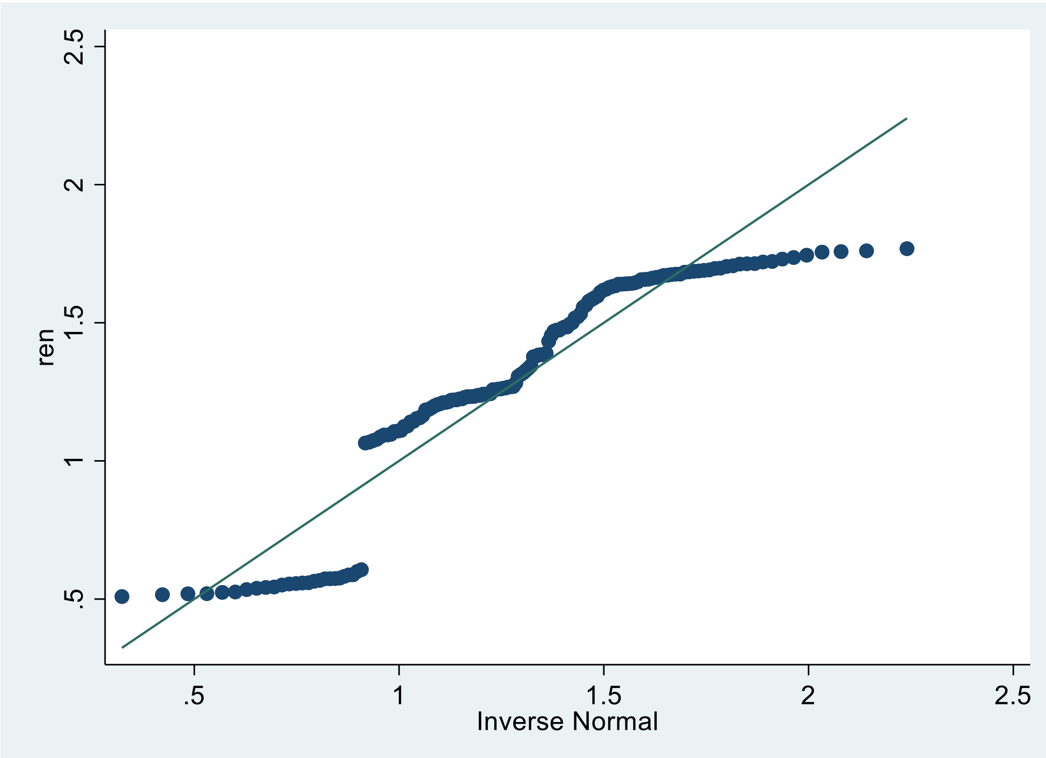

Figure 10: Q-Q plot of urbanization