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Policy debates and controversies

Energy consumption, economic policy uncertainty and carbon emissions; causality evidence from resource rich economies

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ABSTRACT

The study uses the World Uncertainty Index to analyze the long-run relationship of economic policy uncertainty and energy consumption for countries with high geopolitical risk over the period 1996–2017. The Kao test shows a cointegration association between energy consumption, economic growth, geopolitical risk, economic policy uncertainty, and carbon dioxide (CO_2) emissions. The results based on the Panel Pooled Mean Group-Autoregressive Distributed lag model (PMG-ARDL) show that energy consumption and economic growth contribute to (CO_2) emissions. Additionally, there is a significant association between economic uncertainty and CO_2 emissions in the long-run. The panel causality analysis by Dumitrescu and Hurlin (2012) shows a bidirectional relationship between CO_2 emissions and energy consumption, economic policy uncertainty and CO_2 emissions, economic growth and CO_2 emissions, but a unidirectional causality from CO_2 emissions to geopolitical risks. The findings call for vital changes in energy policies to accommodate economic policy uncertainties and geopolitical risks.

1. Introduction

Over the past two decades, the increasing threats of global warming associated with climate change have drawn attention to Greenhouse gas (GHG) emissions, particularly carbon dioxide (CO_2) as the dominant contributor to global warming. The problem of these emissions is more critical in resource rich countries who also experience high levels of economic uncertainty and geopolitical risk. Ten of the highest emitters of CO_2 in this group of countries include the five BRICS countries (Brazil, Russia, India, China, and South Africa), Turkey, Venezuela, Israel, Ukraine, and Saudi Arabia. This group of countries, on the average, emitted about 241029 kt in 1970 and after over half a century in 2014, this figure had increased to 1730154 kt CO_2 (The World Bank, 2019). The tremendous increase in emissions is due to the high economic growth and the subsequent high energy consumption in this group of countries. It is worthy of note that the averages mask the massive differences in CO_2 emissions of these countries because the BRICS contribute more than 80% of the emissions and over the period, the resource rich countries did see an increase in emissions of over 1000% percentage

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points. Obviously, this is relevant when one considers that while CO_2 emissions reduced in the developed countries from about 40% to 25%, it increased in the BRICS from 27% to 42% over the period 1990–2018 (BP, 2019; IISD, 2019).

The Global Energy and CO_2 Status Report (IEA, 2019) shows that due to high energy consumption, CO_2 emissions rose by 1.7% in 2018 to a notable high record of 33.1 Gt CO_2. For instance, China is the largest CO_2 emitter with almost 30% of global greenhouse gas emissions and 60% of the emissions by the resource rich countries. The Environmental Performance Index (EPI), which measures the environmental performance of a country shows that India ranks 177 out of 180 ranked countries, while South Africa, China, Turkey and Ukraine are ranked 142, 120, 108, and 109 respectively. Only Israel is ranked in the top 20 at 19 with the rest of the countries being studied ranked between 50 and 86. However, the Global Green Economy Index [GGEI] (2018), which is a measure of the commitment of nations to reduce CO_2 emissions shows that of the 130 countries ranked, China is the most successful of the group of studied and is ranked 28, followed by Brazil, India, Israel, and Ukraine at 33, 36, 49, and 121 respectively. The GGEI utilizes numerical and non-numerical indicators to assess each country's performance on four key dimensions: leadership and climate change, markets and investment, efficiency sectors and the environment. It is worth mentioning that many studies have examined the determinants of CO_2 emissions or the energy consumption– CO_2 nexus (Ozturk and Acaravci, 2013; Wang and Dong, 2019; Dong et al., 2019) though not much on how policy uncertainty affects the energy consumption–CO_2 emissions. This gap motivates the study.

Global uncertainties have also heightened economic and political policy volatility around the world. Obviously, whatever causes uncertainty (political, social, trade, war or conflict) is likely to have an effect on economic activity (Rodrik, 1991; Guidolin and La Ferrara, 2010; Blattman and Miguel, 2010). An example is the second Gulf war in 2003 which created a lot of economic uncertainty in the global economy (Rigobon and Sack, 2005). More recently, the global pandemic [COVID-19] (a health issue) has induced a lot of economic uncertainty around the world (See Baker et al., 2020; Altig et al., 2020; Bakas and Triantafyllou, 2020). Generally, economic policy uncertainty (EPU) affects the environment in which businesses operate and this in turn affects the decision making of economic entities. This means that since CO_2 emissions are linked to the production decisions of businesses, economic policy uncertainty could have effect on CO_2 emissions (Jiang et al., 2019). Al-Thaqeb and Algharabali (2019), for example, have argued that the significance of uncertainty in policies related to economic decisions is higher in today's fast paced interconnected world. On the other hand, Jiang et al. (2019) suggest that economic policy uncertainty impacts on CO_2 through direct government policy which might promote or hinder environmental degradation.

Levenko (2020) discusses uncertainty as a driver of household savings, while Das et al. (2019) focus on stock market and Xu (2020) considers corporate innovation. Current studies of climate science research suggests that climate dynamics are important in economic analyses and policy guidance (Brock and Hansen, 2018; Contreras and Platania, 2019; Workman et al., 2020). Golub (2020) shows that climate policy uncertainty decreases the probability of an economy to converge to a higher steady state. Indeed, Guo et al. (2019) do argue that both underestimation and overestimation of uncertainties have implications for environmental policy making. This is not surprising because policy uncertainty is expected to have a significant impact on firms' financial policies, investment strategy as well as on consumer spending. Istiak and Alam (2019), Alam and Istiak (2019), and Hassan et al. (2018) also do report that policy uncertainty has nonlinear effect on inflation expectation, US–Mexico relations, and trade flows respectively. However, there is a dearth of empirical literature on how economic uncertainty directly or indirectly affects CO_2 emissions. The study fills this gap in the literature.

Another key indicator that has been debated in the literature is the impact of geopolitical risk on policy making (Caldara and Iacoviello, 2018). Specifically, geopolitical risk refers to factors (political, socioeconomic and cultural) that have the potential to affect the performance of organizations. This variable is particularly important to the resource rich countries that are prone to conflict, war or war-like tensions and terror related conflicts. Recently, Das et al. (2019) and Kannadhasan and Das (2019) have reported that economic policy uncertainty and geopolitical risk have a significant impact on emerging and Asian stock markets. This study is situated in the literature that discusses both the EPU and GPR as critical determinants of the energy consumption, investment decision, economic cycle and overall policy making (Bernanke, 1983), all of which are expected to have a direct or indirect effect on environmental quality. Despite uncertainty's significance to the economic system, earlier studies did not account for this because of the lack reliable measures for uncertainty. With the release of the EPU and GPR by Ahir et al. (2018) and Caldara and Iacoviello (2018) respectively, empirical analyses involving these variables have become possible. Guo et al. (2019) investigate the effect of uncertainties on CO_2 emissions and report that uncertainties generate abatement costs which influence the economic decision-making process. Chen and Kettunen (2017) also report that it is optimal for firms with higher risk aversion to invest more in renewable technologies than their less risk-averse rivals. In a related study, Lecuyer and Quirion (2019) find that renewable energy subsidies are welfare enhancing only when uncertainty is high because CO_2 abatement costs are accounted for in the case of over-allocation.

Additionally, Xu (2020) reports that economic policy uncertainty disrupts organizational decision making. Indeed, Li et al. (2019) using data from 231 Chinese firms companies demonstrate that environmental uncertainties drive green innovation in firms. Innovation's pro-environment effect is based on the assumption that it leads to advances in technology that enhance both product and process efficiencies which reduce CO_2 emissions (Ahmad et al., 2019; Gamso, 2018; Mensah et al., 2018). The brief review provides support to Workman et al.'s (2020) argument that explicitly modeling uncertainty provides more relevant and robust information for climate policy. Afzali et al. (2020), for example, have noted that uncertainty influences the operational cost of the energy system more than performance with respect to energy utilization.

Table 1
Description of data.
Source: WDI is connotation for data from World Bank Development Indicator of the World Bank database sourced from https://data.worldbank.org/.

Name of indicator	Abbreviation	Proxy/Scale of measurement	Source
CO2 Emissions	CO2	Million tonnes of carbon dioxide	BP Statistical Review of World Energy June 2019
Real Gross Domestic Product per capita	RGDP	Constant 2010 US$	WDI
Energy Consumption	ENC	Million tonnes oil equivalent	BP Statistical Review of World Energy June 2019
Geopolitical Risk	GPR	Index	(Caldara and Iacoviello, 2018) https://www2.bc.edu/matteo-iacoviello/gpr.htm.
Economic Policy Uncertainty	EPU	World Uncertainty Index (WUI)	(Ahir et al., 2018) http://www.policyuncertainty.com

Countries	Brazil	China	India	Israel	Russia	Saudi Arabia	South Africa	Turkey	Ukraine	Venezuela
Abbreviation	BRA	CHN	IND	ISR	RUS	SAU	ZAF	TUR	UKR	VEN

Note. WUI = This tab contains the beta version of the historical World Uncertainty Index (WUI) for 82 countries from 1952Q1 to 2019Q3. The tab contains a moving average index. The 3-quarter weighted moving average is computed as follows: 1996Q4 = (1996Q4*0.6) + (1996Q3*0.3) + (1996Q2*0.1)/3.

Accordingly, the objective of the study is to examine how the economic policy uncertainty and geopolitical risks affect the energy consumption–CO_2 emissions relationship. In achieving the research objective, the study makes three main contributions to the extant literature. First, we account for economic policy uncertainty in the energy consumption–CO_2 emissions relationship to reduce estimation bias. Second, we improve the estimates further by modeling for the geopolitical risk factors, which are predominant among resource rich countries. Additionally, focusing on countries with similar geopolitical characteristics helps to improve the consistency and efficiency of the estimates. Third, the long run elasticity of economic policy uncertainty and geopolitical risks are determined for the individual countries in the panel and takes into account both the time and cross-sectional dimensions to give more robust results.

In the section that follows, the data and methodology are described, the results are presented and discussed, conclusions given and policy recommendations offered.

2. Data and methodology

2.1. Data

The data for this study covers the period 1996–2017 for 10 resource rich countries, including Brazil; China; India; Israel; Russia; Saudi Arabia; South Africa; Turkey; Ukraine; and Venezuela. The data sources are described in Table 1. The selection of variables is motivated by the Environmental Kuznets Curve Hypothesis. However, as a novelty, we introduce economic policy uncertainty index and geopolitical risks in the EKC model to test how these variables affect CO_2 emissions.

2.2. Model specification

The study utilizes EKC model in an ARDL framework. The builds on previous studies on the energy consumption–emissions nexus (Akadiri et al., 2019; Alola et al., 2019; Bekun et al., 2019a,b; Emir and Bekun, 2019), by testing the moderating effects of geopolitical risks and economic policy uncertainties (See Eq. (1)). Preliminary analysis was carried out to study the data trends. In depth analysis commenced with Pesaran cross-sectional independence test, which was followed by correlation matrix to test the strength of the relationships. The ADF–Fisher and IPS and Pedroni and Kao tests were used to examine the stationary and cointegration respectively to avoid spurious regressions and validate the long-term relationships for the PMG-ARDL analysis and Dumitresu–Hurlin panel causality.

$$\mathrm{CO2} = f\,(\mathrm{ENC}, \mathrm{RGDP}, \mathrm{RGDP2}, \mathrm{GPR}, \mathrm{EPU}, \mathrm{ENC} * \mathrm{GPR}, \mathrm{ENC} * \mathrm{EPU}) \tag{1}$$

$$\mathrm{LCO2}_{it} = \alpha_0 + \beta_1 \mathrm{LRGDP}_{it} + \beta_2 \mathrm{LRGDPSQ}_{it} + \beta_3 \mathrm{LENC}_{it} + \beta_4 \mathrm{LGPR}_{it} + \beta_5 \mathrm{LEPU}_{it} + \beta_6 \mathrm{LENCEPU}_{it} + \beta_7 \mathrm{LENCGPR}_{it} + \varepsilon_{it} \tag{2}$$

Logarithmic transformation (L) is carried out on all variables so as to have a constant variance for the series. LCO_2 represent CO_2 Emissions; LRGDP represents Real Gross Domestic Product per capita; LENC is Energy Consumption; LGPR represents Geopolitical Risk; LEPU represents Economic Policy Uncertainty; α_0 is the intercept; $\beta_1 \ldots \beta_7$ represents the partial slope coefficients of the variables; ε is the error term; i represents the countries and t is the time period. Because of potential bias activated in the mean-differenced explanatory factors and the term representing error term, standard ARDL estimation models are unequipped for controlling these potential biases particularly in panel data framework which seeks to show individual impacts. In such cases, a mix of ARDL model and PMG estimator by Pesaran et al. (1999) helps to

Table 2
Summary statistics.

Individual country mean (1996–2017)					
	LCO2	LRGDP	LENC	LGPR	LEPU
Brazil	5.89	9.21	5.42	4.56	−2.60
China	8.68	8.07	7.50	4.61	−4.06
India	7.21	7.04	6.09	4.49	−3.47
Israel	4.19	10.28	3.08	4.49	−2.89
Russia	7.31	9.08	6.48	4.64	−2.71
Saudi Arabia	5.96	9.87	5.12	4.60	−3.55
South Africa	5.98	8.82	4.73	4.51	−2.56
Turkey	5.53	9.22	4.55	4.72	−2.38
Ukraine	5.69	7.84	4.81	4.66	−2.60
Venezuela	5.01	8.72	4.30	4.50	−2.66
Group summary statistics (1996–2017)					
Variable	Obs.	Mean	Std. Dev.	Min	Max
LCO2	220	6.14	1.24	3.98	9.13
LRGDP	220	8.81	0.96	6.57	10.44
LENC	220	5.21	1.20	2.85	8.05
LGPR	220	4.58	0.25	3.65	5.57
LEPU	218	−2.94	0.85	−7.74	−0.87

Table 3
Cross sectional dependency result.

Test	Statistic	Prob.
Pesaran's test of cross-sectional independence	1.548	0.1217

Note. Null hypothesis: cross-sectional independence (CD ∼ (0, 1). Prob.

deal with the problem (Sarkodie and Strezov, 2018). In opposition to models used in previous studies, the current study adopts the Panel Pooled Mean Group-Autoregressive Auto regressive distributed lag model (PMG-ARDL) model given as:

$$\Delta Ly_{it} = \emptyset_i ECT_{it} + \sum_{j=0}^{q-1} \Delta Lx_{it-j}\beta_{ij} + \sum_{j=1}^{p-1} \psi_{ij}\Delta Lx_{it-j} + \varepsilon_{it} \tag{3}$$

$$ECT_{it} = y_{it-1} - X_{it}\theta \tag{4}$$

In both Eqs. (3) and (4), y stands for the explained variable (i.e. LCO_2), X is the vector for the list of explanatory variables (i.e. ENC, RGDP, GPR, EPU) all of which have the same lag q which runs across the countries i in time t. The difference operator is captured by Δ, while θ stands for coefficient of the long run which yields estimates of β and ψ at convergence. Apart from conducting descriptive statistical analysis, three important pre- and post-estimation diagnostics are carried out: (i) Both Im et al. (2003) and Fisher ADF test for stationarity among the series; (ii) Analysis of cointegration as well as long run relationship following Pesaran et al. (1999); (iii) The recent Dumitrescu and Hurlin (2012) causality tests.

3. Results and discussion

The primary attributes of the natural log of CO_2, real gross domestic product, energy consumption, geopolitical risks and economic policy uncertainty are reported in Table 2. Of the ten countries considered, Israel has the highest average economic growth, followed by Saudi Arabia, Russia and Brazil. China takes the lead in terms of average CO_2 emissions while Israel records the least. The ten countries share similar average geopolitical risk. Meanwhile, a close look at the result reveals a high level of EPU in China, Saudi Arabia and India. For group summary statistics, the real gross domestic product shows highest average value of 8.81, while economic policy uncertainty has a negative average value of 2.94. Except for CO_2 emissions and energy consumption that exhibit higher mean dispersion of 1.24 and 1.20, respectively, other variables show lower variability.

3.1. Pesaran's test of cross-sectional independence

The Cross-sectional dependence (CD) test provides information on whether the individual observations in the dataset are related or not and it gives a clear direction on the co-integration test, unit root test and analytical technique most suitable for the panel data analysis. Pesaran CD test is used to test the conjecture of cross-sectional independence in this study and the result provided in Table 3 shows that the p-value of the CD test statistic exceeds 5%, which implies the absence of CD.

Table 4
Result of Pearson correlation matrix.

	LCO2	LRGDP	LENC	LGPR	LEPU
LCO2	1				
	–				
LRGDP	−0.4961***	1			
	0.0000				
LENC	0.9827***	−0.4661***	1		
	0.0000	0.0000			
LGPR	0.0654	0.0298	0.0803	1	
	0.3345	0.6600	0.2354		
LEPU	−0.3605***	0.1759***	−0.3282***	0.0838	1
	0.0000	0.0093	0.0000	0.2177	

***; **; and * connotes a statistical rejection level of normality test statistics at 1%; 5% and 10% significance levels respectively.

Table 5
Results of unit root tests.

Test	IPS		ADF–FISHER	
Variable	Level	Δ	Level	Δ
LCO2	−0.1880	−6.9659***	1.6920	−4.9089***
LRGDP	1.5840	−5.2932***	2.6938	−4.8173***
LENC	−0.2484	−6.9089***	2.4327	−5.2494***
LGPR	−4.0715***	−8.0932***	−3.1894***	−8.9931***
LEPU	−5.4660***	−8.1206***	−4.6299***	−10.9898***
LENCGPR	−4.6792***	−8.3120***	−2.7463***	−9.8483***
LENCEPU	−5.3169***	−8.0805***	−4.6457***	−10.7934***

Notes: Δ is first difference operator for the model with both trend and intercept at level. Lag length is automatically selected using Akaike information criterion. ***, ** and * represents a rejection of the null hypothesis of "unit root" at the 1%, 5% and 10% levels of significance respectively.

3.2. Pearson correlation matrix

Further, the study employs the Pearson correlation matrix to determine the nature and strength of the relationship between the variables (Table 4). Energy consumption is positive and significantly correlated with CO_2 emission, while the EPU and economic growth are negatively signed and GPR is insignificantly related. Additionally, a thorough inspection of the relationship between the independent variables reveals the absence of multicollinearity problem.

3.3. Stationary and cointegration tests

Augmented Dickey–Fuller–Fisher (ADF–Fisher) and Im–Pesaran–Shin (IPS) stationary tests which are suitable for unbalanced panel dataset are used to determine the order at which carbon dioxide, growth, energy consumption, geopolitical risks, and economic policy uncertainty become stationary. The results of the two tests reported in Table 5 are similar. The IPS and ADF–Fisher tests reveal that energy consumption, CO_2 and economic growth are integrated at first difference while geopolitical risks and economic policy uncertainty are stationary at levels.

Having established the order of stationarity, Pedroni cointegration test is utilized to validate cointegration of the variables. The p-value of the Kao cointegration t-static is less than 5%. This authenticates the results of the Pedroni cointegration test. (See Table 6.)

3.4. Results of MG-ARDL and PMG-ARDL

The study reports results of PMG-ARDL and the MG-ARDL. The **PMG** and MG estimations account for cross-sectional heterogeneity through the short-term parameters and facilitate both long-run and short-run causality inferences to be drawn, regardless of whether the variables used are integrated of order one or zero I(1) or I(0). The difference between them is that while the MG allows all coefficients to vary as well as to be heterogeneous in the short and long-run, the PMG imposes a homogeneity restriction on long run coefficients. However, according to Pesaran et al. (1999), the PMG estimator offers an increase in the efficiency estimates as compared to the MG estimator under the long-run homogeneity. The Hausman test is used to test the null hypothesis (H_0) (both MG and PMG are consistent, but MG is inefficient), and the alternate (H_a) will indicate that PMG is inconsistent. If p-value >5% PMG is used while when p-value < 5% MG method is more appropriate. The Hausman test shows a p-value of 0.1542 and therefore the null could not be rejected indicating the PMG is preferred (See Table 7). The results of the PMG-ARDL (1, 1, 1, 1, 1) for the three models provided in Table A.2 are similar for the error correction term in terms of significance, size and sign. The values of the error correction terms

Table 6
Results of Pedroni and Kao cointegration tests.

Statistic	Statistic	Prob
Pedroni cointegration test		
Panel v-Statistic	−0.1181	0.4529
Panel Rho-Statistic	0.2025	0.5802
Panel PP-Statistic	−2.49	0.0063***
Panel ADF-Statistic	−2.27	0.0116***
Group Rho-Statistic	1.391	0.9178
Group PP-Statistic	−2.098	0.0179***
Group ADF-Statistic	−1.784	0.0372***
Kao cointegration test		
	t-Stat	Prob.
ADF	2.4060	0.0081***

Notes: Dependent variable = CO_2 Emissions. v, rho, PP, ADF statistics are measured using Pedroni (2004) and Pedroni (1999). *p* values are given in parentheses. PP = Phillips–Perron; ADF = Augmented Dickey–Fuller. *** and ** represents a statistical rejection level of the null of no cointegration at 1% and 5% significance level respectively.

for the three models are positive, less than one and significant at 1%. The resultant effect of this finding is that in the case of structural change or shock, about 43%, 36% and 45% of the disequilibrium of the first, second, and third models respectively diverge rather than converge to the long-run equilibrium.

The first model shows that in the short run, real gross domestic product is not significant. However, one percent increase in the real gross domestic product in the long run significantly worsens the environmental quality by 0.201%. The findings of this research is similar to that of Adams and Nsiah (2019) and Adams and Klobodu (2018) for SSA countries as well as the findings of Belaïd and Zrelli (2019) and Waqih et al. (2019) for Mediterranean countries and South Asian Association for Regional Cooperation (SAARC) region respectively. The implication is that a boom in economic activities will degrade the environment of the resource-rich countries. However, the result contradicts the work of Shahbaz et al. (2019) for Vietnam. The lack of unanimity in the result could be attributed to the difference in the scope of the study.

The square of real gross domestic deteriorates the environmental quality in the short-run (0.03%), though it significantly decreases CO_2 emission by 0.02% in the long-run. Further, the result shows that the prediction of the Environmental Kuznets Curve is constant in the long-run while the U-shape curve is prevalent in the short-run. The implication of the U-shape is that environmental degradation decreases at the early stages of economic boom and increases after the turning point (Shahbaz et al., 2019). For energy consumption, there is a linear relationship such that CO_2 emissions increase significantly by 1% for every 1% increase in energy consumption both in the short- and long-run. This implies that irrespective of the energy efficiency policy pursued by the resource-rich but crisis-prone economies in the short- and long-run, energy consumption aggravates environmental quality at the same rate. This finding is in line with large number of empirical studies on the relationship between energy consumption and economic growth (Acheampong et al., 2019; Adams et al., 2018, 2016). Geopolitical risk exerts no significant effect on carbon dioxide emission in the short run. Economic policy uncertainty increases CO_2 emissions by 0.002% and 0.012% in the short- and long-run respectively. This is not unexpected as firms' cash-flow, cash-holding and external financing have been proven to be negatively affected by economic policy uncertainty. It is worthy of note that even though economic policy uncertainty contributes to CO_2 emissions, the effect is far less than the effect of energy consumption.

The second model shows the result of the analysis when geopolitical risk is excluded from the model. Keeping other variables constant, a 1% increase in economic growth adversely affects the environment by 0.35% in the long run, which supports the findings of Khan et al. (2019). On the contrary, the square of economic growth significantly improves environmental quality by 0.03% in the long-run, though it exerts an insignificant positive effect on CO_2 emissions in the short-run. The significant effect of the square of economic growth on CO_2 emission in the long-run implies that policy makers in the resource-rich countries could address the problem of environmental degradation by formulating policies that promote efficient use of CO_2 emission materials during the production processes. Energy consumption is positive and significant at 1% in the short- and long-run. So, an additional 1% increase in the level of energy consumption is associated with 1.05% and 1.03% increase in emission in the short- and long-run respectively, holding other factors constant. Hanif et al. (2019), Gorus and Aydin (2019) and Shahbaz et al. (2019) also reported similar results for Asian economies, MENA region, and Vietnam respectively. Moreover, in the second model, we find that policy uncertainty degrades the environment by 0.002% and 0.011% in the short-run- and long-run, respectively.

The results of the third model reveal that economic growth is not significantly related to economic growth, which is inconsistent with the results of the first and second models. The square of economic growth enhances environmental quality in the short- and long-run. The relationship between geopolitical risk and CO_2 emission is similar to the first model. Geopolitical risk only has a significant positive effect on carbon emission in the long-run, even though the result is also plausible in the short-run. For sensitivity of our variables in the model, we test interaction of EPU with energy consumption as well as GPR with energy consumption in the selected countries. The results are not different from the earlier findings suggesting that the results are robust.

Table 7
Results of PMG/MG ARDL estimation. Dependent variable: Log CO_2.

Panel A : Long-run estimates									
Pooled Mean Group						Mean Group			
Variable	Model 1	Model 2	Model 3	Sensitivity analysis		ECT	SR	ECT	SR
Constant	−0.285***	0.0697*	−0.411***	0.598***	−0.399***		−0.436***		−0.254***
	(0.0962)	(0.0385)	(0.126)	(0.231)	(0.128)		(0.134)		(0.0807)
LRGDP	0.201*	0.354**	0.144*	0.615	0.158*	0.134		0.117	
	(0.107)	(0.177)	(0.0827)	(0.441)	(0.0891)	(0.0838)		(0.155)	
LRGDPSQ	−0.0184***	−0.0276***	−0.0149***	−0.0336	−0.0156***	−0.0143***		−0.00499	
	(0.00643)	(0.0102)	(0.00499)	(0.0255)	(0.00540)	(0.00505)		(0.00893)	
LENC	1.014***	1.032***	0.999***	0.951***	0.989***	0.999***		0.917***	
	(0.0136)	(0.0178)	(0.0124)	(0.0330)	(0.0454)	(0.0123)		(0.0137)	
LGPR	−0.0345***		−0.0320***		−0.0406	−0.0336***			
	(0.00740)		(0.00625)		(0.0445)	(0.00643)			
LEPU	0.0116***	0.0112**		−0.0350		0.00388		0.00315	
	(0.00400)	(0.00459)		(0.0376)		(0.00304)		(0.00346)	
LENCEPU				0.00934					
				(0.00758)					
LENCGPR					0.00146				
					(0.00903)				
Panel B: Short run estimates									
Pooled Mean Group						Mean Group			
Variable	Model 1	Model 2	Model 3	Sensitivity analysis		ECT	SR	ECT	SR
ECT(−1)	0.430***	0.366***	0.448***	0.345***	0.442***		0.445***		0.406***
	(0.131)	(0.107)	(0.135)	(0.131)	(0.138)		(0.132)		(0.128)
LRGDP	−0.0818	−0.700	0.640	−0.639	1.566		0.522		−1.597
	(5.773)	(5.441)	(6.363)	(5.765)	(5.935)		(5.834)		(5.694)
LRGDPSQ	0.0250	0.0574	−0.0173	0.0641	−0.0640		−0.0106		0.104
	(0.306)	(0.288)	(0.339)	(0.301)	(0.314)		(0.310)		(0.304)
LENC	1.020***	1.048***	1.000***	1.031***	0.984***		1.019***		1.053***
	(0.0573)	(0.0545)	(0.0665)	(0.0564)	(0.198)		(0.06)		(0.05)
LGPR	0.00428		0.00362		0.00308		0.00		
	(0.00810)		(0.00844)		(0.210)		(0.01)		
LEPU	0.00195	0.00211		0.0336			0.00		0.00
	(0.00218)	(0.00230)		(0.0864)			(0.00)		(0.00)
LENCEPU				−0.00798					
				(0.0169)					
LENCGPR					0.00542				
					(0.0490)				
Hausman test-statistic							0.591		
Hausman *p*-value							0.1542		

Note: The fitted model is based on maximum lag 1 as suggested by Akaike information criterion. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represents a statistical rejection level of the null hypothesis of no co-integration at 1%, 5% and 10% respectively.
Hausman test results MG and PMG.
H_0: PMGE estimator is efficient and consistent but MGE is not efficient.
Since we could not reject the null hypothesis, the PMG is selected because it provides efficient and consistent estimators. In other words, based on the Hausman test, it is evident that the PMG method is more efficient and consistent than the MG method. Additionally, PMG allows for heterogeneity in the short run, consequently, we select this model and we rely on its estimates.

3.5. Dumitrescu and Hurlin panel causality

The Dumitrescu and Hurlin (2012) panel causality result presented in Table 8 suggests a two-way causal relationship between (1) Growth of the economy and CO_2 emissions; (2) energy consumed and CO_2 emission; (3) economic policy uncertainty and CO_2 emission; (4) economic growth and energy consumed; and (5) policy uncertainty and energy consumption. These findings imply that there is a bidirectional relationship between the variables. The feedback relationship between energy consumed and CO_2 emission supports the work of Pata (2018). However, it is contradictory to the work of Liu et al. (2017) and Pandey and Rastogi (2019) who reported a conservational hypothesis from energy consumption and CO_2 emissions. Belaïd and Zrelli (2019) and Khan et al. (2019) also reported a feedback relationship between energy consumption and CO_2 emission for nine Mediterranean Countries.

Furthermore, the implication of the bidirectional relationship between economic policy uncertainty (EPU) and carbon emission (CO_2) is that policy uncertainty increases firms' cost of production and lower their investment in R&D which in turns limits innovations to reduce carbon emissions. Similarly, poor environmental quality forces the government to formulate environmental-friendly policies which can either limit firms' production capacity or decrease their profits due to higher taxes. The results further display a one-way causality from (1) carbon emissions to geopolitical risk, (2) economic

Table 8
Results of the Dumitrescu and Hurlin (2012) Panel causality.

Null hypothesis	W-Stat.	*P*-value	Causality flow
LRGDP ≠ > LCO2 LCO2 ≠ > LRGDP	3.7579*** 4.5956***	0.0000 0.0000	LRGDP ↔ LCO2
LENC ≠ > LCO2 LCO2 ≠ > LENC	5.5847*** 6.9854***	0.0000 0.0001	LENC ↔ LCO2
LGPR ≠ > LCO2 LCO2 ≠ > LGPR	0.7118 3.5715***	0.5192 0.0000	LCO2 → LGPR
LEPU ≠ > LCO2 LCO2 ≠ > LEPU	0.1808* 1.8797**	0.0670 0.0492	LEPU ↔ LCO2
LRGDP ≠ > LENC LENC ≠ > LRGDP	4.0651*** 3.5816***	0.0000 0.0000	LRGDP ↔ LENC
LRGDP ≠ > LGPR LGPR ≠ > LRGDP	2.4296*** 1.5545	0.0014 0.2150	LRGDP → LGPR
LRGDP ≠ > LEPU LEPU ≠ > LRGDP	2.0165*** 1.1528	0.0230 0.7327	LRGDP → LEPU
LENC ≠ > LGPR LGPR ≠ > LENC	3.4537*** 0.3775	0.0000 0.1639	LENC → LGPR
LENC ≠ > LEPU LEPU ≠ > LENC	1.7999* 0.1522*	0.0737 0.0580	LENC ↔ LEPU
LEPU ≠ > LGPR LGPR ≠ > LEPU	1.2642 1.5582	0.5546 0.2120	LEPU ≠ LGPR

Note: ***, **, * represent 0.01,0.05 and 0.10 rejection levels respectively;
≠, → and ↔ represent No Granger causality, one-way causality and bi-directional causality, respectively.

growth to geopolitical risk, (3) economic growth to economic policy uncertainty, (4) energy consumption to geopolitical risk and (5) energy consumption to economic policy uncertainty.

4. Conclusion and policy implications

This study analyzed the effect of energy consumption, economic policy uncertainty and geopolitical risks on carbon dioxide emissions in resource-rich but crisis-prone economies. The findings of the study based on PMG-ARDL suggest that energy consumption, economic policy uncertainty and economic growth contribute to CO_2 emissions. This implies that higher levels of economic policy uncertainties adversely affect environmental sustainability for countries with higher levels of geopolitical risks. From the literature reviewed and the findings of the study, three main policy implications are derived.

First, is the observation that despite the level of policy uncertainty, political uproar and unrest in the resource rich countries, the result of the preliminary analysis shows that Israel, Saudi Arabia, Russia and Brazil recorded high economic growth. The cointegration tests revealed a long-run relationship for all variables and the results of the three models uncover the adverse effect of energy consumed on CO_2 emission in the short- and long-run. These findings are consistent with those of Alam et al. (2016), Sarkodie et al. (2020) and Sharif et al. (2019) as the improvement in incomes is associated with a higher standard of living and the demand for more energy consuming products with high carbon dioxide emissions. Accordingly, to reduce CO_2 emissions, the government of the countries concerned should be encouraged to promote the use of renewable energy or clean energy sources (Qiao et al., 2019; Sharif et al., 2019). This will require high level of investment in R&D to promote the necessary technologies for the development and design of more efficient energy systems to decouple economic growth from environmental pollution.

Second, economic policy uncertainty aggravates CO_2 emissions in the resource-rich but crisis-prone economies. This does not come as a surprise as economic policy uncertainty deters capital investment in energy-efficient machinery (and appliances) and innovation capable of reducing carbon emissions. It is therefore reasonable for the countries to promote economic policy that encourages innovation and stimulate capital investment in energy efficiency equipment or appliances. Finally, political uproar and unrest should be adequately addressed to reduce its effect on emissions.

Third, related to the second point is the principle that in the midst of uncertainty, it is difficult to come up with workable solutions. Thus, ignoring uncertainty could lead to mis-specification or quantification of the energy consumption–CO_2 emissions relationship. In such a case, undue actions may bring about irreversible investment and thus negatively affect the intended decision-making process in the long-term. For instance, overestimation of the uncertainty deters the incentive to invest in low-carbon projects, and hence heightens the risk of locking into existing fossil-fuel-based economy structure. However, underestimation of the uncertainty can squander the chance for an early-mover advantage, which could lay the foundation for stronger and potentially more sustainable growth (Guo et al., 2019; Workman et al.,

Table A.1
Mean Group ARDL estimates.

Mean Group ARDL estimates				
VARIABLES	ECT	SR	ECT	SR
ECT (−1)		0.445***		0.406***
		(0.132)		(0.128)
D.LRGDP		0.522		−1.597
		(5.834)		(5.694)
D.LRGDPSQ		−0.0106		0.104
		(0.310)		(0.304)
D.LENC		1.019***		1.053***
		(0.0611)		(0.0494)
D.LGPR		0.00467		
		(0.00813)		
D.LEPU		0.000615		0.00138
		(0.00190)		(0.00262)
LRGDP	0.134		0.117	
	(0.0838)		(0.155)	
LRGDPSQ	−0.0143***		−0.00499	
	(0.00505)		(0.00893)	
LENC	0.999***		0.917***	
	(0.0123)		(0.0137)	
LGPR	−0.0336***			
	(0.00643)			
LEPU	0.00388		0.00315	
	(0.00304)		(0.00346)	
Constant		−0.436***		−0.254***
		(0.134)		(0.0807)

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Hausman test results MG and PMG.
H_0: PMGE estimator is efficient and consistent but MGE is not efficient.
P-Value = 0.1542.
Since we could not reject the null hypothesis, the PMG is selected because it provides efficient and consistent estimators. In other words, based on the Hausman test, it is evident that the PMG method is more efficient and consistent than the MG method. Additionally, PMG allows for heterogeneity in the short run, consequently, we select this model and we rely on its estimates.

2020). It is therefore recommended that evaluation of environmental policy should always take into account economic policy uncertainty to provide more robust information for climate policy oriented towards reducing CO_2 emissions.

Finally, future research should focus on examining the various types of uncertainty in terms of the risk, ambiguity and mis-specification and quantify them appropriately and more importantly their differential effects, if any, to provide evidence informed climate policy.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. List of abbreviations

CO_2—Carbon Emissions
PMG-ARDL—Pooled Mean Group Autoregressive Distributed Lag Model
MENA—Middle East and Northern Africa Region
EKC—Environmental Kuznets Curve
EPU—Economic Policy Uncertainty
GPR—Geopolitical risks
CD—Cross sectional dependence
R&D—Research and Development
SAARC—South Asian Association for Regional Cooperation region

See Tables A.1 and A.2.

Table A.2
Result of PMG-ARDL (1, 1, 1, 1, 1).

VARIABLES	Model 1	Model 2	Model 3	Sensitivity analysis	
Short run					
ECT (−1)	0.430***	0.366***	0.448***	0.345***	0.442***
	(0.131)	(0.107)	(0.135)	(0.131)	(0.138)
LRGDP	−0.0818	−0.700	0.640	−0.639	1.566
	(5.773)	(5.441)	(6.363)	(5.765)	(5.935)
LRGDPSQ	0.0250	0.0574	−0.0173	0.0641	−0.0640
	(0.306)	(0.288)	(0.339)	(0.301)	(0.314)
LENC	1.020***	1.048***	1.000***	1.031***	0.984***
	(0.0573)	(0.0545)	(0.0665)	(0.0564)	(0.198)
LGPR	0.00428		0.00362		0.00308
	(0.00810)		(0.00844)		(0.210)
LEPU	0.00195	0.00211		0.0336	
	(0.00218)	(0.00230)		(0.0864)	
LENCEPU				−0.00798	
				(0.0169)	
LENCGPR					0.00542
					(0.0490)
Long run					
LRGDP	0.201*	0.354**	0.144*	0.615	0.158*
	(0.107)	(0.177)	(0.0827)	(0.441)	(0.0891)
LRGDPSQ	−0.0184***	−0.0276***	−0.0149***	−0.0336	−0.0156***
	(0.00643)	(0.0102)	(0.00499)	(0.0255)	(0.00540)
LENC	1.014***	1.032***	0.999***	0.951***	0.989***
	(0.0136)	(0.0178)	(0.0124)	(0.0330)	(0.0454)
LGPR	−0.0345***		−0.0320***		−0.0406
	(0.00740)		(0.00625)		(0.0445)
LEPU	0.0116***	0.0112**		−0.0350	
	(0.00400)	(0.00459)		(0.0376)	
LENCEPU				0.00934	
				(0.00758)	
LENCGPR					0.00146
					(0.00903)
Constant	−0.285***	0.0697*	−0.411***	0.598***	−0.399***
	(0.0962)	(0.0385)	(0.126)	(0.231)	(0.128)

Note: The fitted model is based on maximum lag 1 as suggested by Akaike information criterion. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ represents a statistical rejection level of the null hypothesis of no co-integration at 1%, 5% and 10% respectively.

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