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

Abstract

The study uses the new World Uncertainty Index to analyze the causality and long-run effects of economic policy uncertainty and energy consumption in a carbon function 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 emissions (CO_2). The results based on the Panel Pooled Mean Group-Autoregressive Auto regressive distributed lag model (PMG-ARDL) show that energy consumption and economic growth trigger carbon emissions. Additionally, there is a significant association between economic uncertainties and CO_2 emissions in the long-run, while this relationship is negative for geopolitical risks. This implies that higher levels of economic policy uncertainties adversely affect environmental sustainability for countries with higher levels of geopolitical risks. The panel causality analysis by Dumitrescu and Hurlin (2012) identifies 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. Our findings call for the need for vital changes in energy policies to accommodate economic policy uncertainties and geopolitical risks.

Keywords: Energy Consumption; Carbon dioxide emissions; Geopolitical Risk; Economic Growth; Economic Policy Uncertainty.

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 many resource rich countries who also experience high levels of economic uncertainty and geopolitical risk. Ten of the most popular 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 120392 kt of CO_2 in the 1960s, increased to 241029 in 1970s, 403497 in the 1980s, 697968 in the 1990s, and 1037706 in the first decade in the 2000s and by 2014 emitted 1730154 kt CO_2 (The World Bank, 2019). The tremendous growth in emissions is due to the high 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 as the BRICS contribute more than 80% of the emissions and over the period, the resource rich countries have seen an increase in emissions of over 1000% percentage points. Obviously, this is worth studying when one considers that while CO_2 emissions reduced in the developed countries from about 40% to 25%, it increased in the BRICS region from 27% in 1990 to 42% in 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 is a measure of marking and quantifying the environmental performance of a state's policies shows that India ranks 177 out of 180 ranked countries, while South Africa is ranked 142 and China at 120, Turkey at 108 and Ukraine at 109. Only Israel is ranked in the top 20 at 19 with the rest ranging between 50 and 86. However, the Global Green Economy Index [GGEI] (2018) shows that of the 130 countries ranked, China is the most successful of the group of studied at 28, followed by Brazil at 33, India at 36 and Israel at 49 with the least commitment by Ukraine at 121. The GGEI utilizes numerical and non-numerical indicators to assess each country's performance on four key dimensions: leadership & climate change, markets & investment and the environment and efficiency sectors. It is worth mentioning that many studies have examined the determinants of CO_2 emissions or the energy consumption –carbon emissions nexus (Ozturk & Acaravci, 2013; Wang and Dong, 2019; Dong et al., 2019) though not much on how the policy space particularly policy uncertainty affects the energy consumption – carbon dioxide emissions. This gap motivates the study.

Global uncertainties have also heightened economic and political policy volatility around the world. As a global village, effects of uncertainty in one part of the globe can spiral to further complexities which create greater uncertainty as seen in the Brexit debate, US-China Trade conflict, and Global financial crisis of 2008 (Al-Thaqeb et al., 2019). Obviously, economic policy uncertainty (EPU) affects the environment of business which 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 than ever before 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.

Levonko (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 the climate dynamics is important in economic analysis and policy guidance (Brock & Hansen, 2018; Contreras & 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) have argued that both underestimation and overestimation of uncertainties have implications for environmental policy making. This is not surprising because, overall, policy uncertainty has a significant impact on firm financial policies, investment strategy as well as on consumer spending, all of which could have an effect on energy consumption and consequently carbon dioxide emissions. Istiak and Alam (2019), Alam and Istiak (2019) and Hassan et al. (2019) 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 carbon dioxide emissions more specifically and climate policy, more generally. The study fills this gap in the literature. This is relevant because uncertainty has implications for both transmissions and inter-temporal valuation. This means that the exact effect of policy uncertainty on CO_2 emissions is an empirical matter that cannot be determined *apriori*, which gives credence to this study.

Another key indicator that has been debated in the literature is the impact of geopolitical risk to policy making (Caldara & Lacoviello, 2017). 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 analysis involving these variables have become possible. Guo et al. (2019) investigate the effect of uncertainties on carbon emissions and report that uncertainties generate abatement costs which influence economic decision-making process. Chen and Kettunen (2017) examine the issue of whether or not certainty is better than uncertainty for CO_2 emissions and 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 only welfare enhancing when uncertainty is high because CO_2 abatement costs are accounted for in the case of over-allocation.

Xu (2020), on the other hand, has shown that prevailing economic policy uncertainty disrupts through the traditional investment irreversibility channel as well as the cost-of-capital channel. Indeed, Li et al. (2019) using data from 231 China-based 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 and a consequent reduction in 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 would provide more relevant and robust information for environmental or climate policy. Indeed, Afzali et al. (2020), for example, have noted that uncertainty influences the operational cost of the energy system more than the performance with respect to energy utilization. Accordingly, the objective of the study is to examine how the economic policy uncertainty and geopolitical risk 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 – carbon dioxide relationship to reduce estimation bias. Second, we improve the estimates further by modeling for the geopolitical risk factors, which are predominant for 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 and the panel, which help to account for both the time and cross sectional dimension and consequently more robust results.

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

2. Data and Methodology

2.1 Data

The data for this study covers the period 1996 to 2017 for 10 resource rich countries, including Brazil; China; India; Israel; Russia; Saudi Arabia; South Africa; Turkey; Ukraine; and Venezuela. Data was extracted from World Bank Development Indicator database, British Petroleum Database, and the database of the index of geopolitical risk and economic policy uncertainty as shown in Table 1. Additionally, 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. The selection of countries is first based on resource rich countries. However, for these countries to qualify to be selected in the sample, they must be countries prone to high geopolitical risks which is selected from the GPR data adapted from Ahir et al. (2018). The gap filled in this study is therefore strengthened by also capturing EPU which is given by global economic uncertainties arising from several issues such as political (Venezuela crisis), economic, and trade uncertainties (such as the China-USA trade war, which commenced in 2017 but became a full-grown crisis in early 2018) amongst other crisis. Consequently, only 10 resource rich countries where used in the study due to the mix of geopolitical risks data availability on one hand and countries that are rich in resources on the other hand.

Table 1. Description of Data and measurement Units

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

2.2 Model Specification

This study utilizes the relationship specified in line with the EKC hypothesis in an ARDL framework following other studies such as Adedoyin et al. (2020a), Adedoyin et al. (2020b) and Bekun et al. (2019). Although several studies have documented the energy consumption-emissions nexus (Akadiri et al., 2019; Alola et al., 2019; Bekun et al., 2019a, 2019b; Emir and Bekun, 2019), the current study departs from such studies by testing the direct and interaction effects of geopolitical risks and economic policy uncertainties on energy consumption on CO_2 emissions (See Equation 1). Preliminary analysis was carried out to study the data trends. In depth analysis commenced with Pesaran cross-sectional independence to any interrelationship between individual data in the panel set, 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.

$$CO2 = f\,(ENC, RGDP, RGDP2, GPR, EPU, ENC * GPR, ENC * EPU) \qquad (1)$$

$$LCO2_{it} = \alpha_0 + \beta_1 LRGDP_{it} + \beta_2 LRGDPSQ_{it} + \beta_3 LENC_{it} + \beta_4 LGPR_{it} + \beta_5 LEPU_{it} + \beta_6 LENCEPU_{it} + \beta_7 LENCGPR_{it} + \varepsilon_{it} \qquad (2)$$

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 connection to 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 capacity, a mix of ARDL model and PMG estimator by Pesaran et al. (1999) help to deal with the problem (Sarkodie & Strezov, 2018). In opposition to models used in previous studies (Sarkodie and Strezov, 2019; Destek and Sarkodie, 2019), the current study adopts the Panel Pooled Mean Group-Autoregressive Auto regressive distributed lag model (PMG-ARDL) model used in Sarkodie and Strezov (2018) and Bekun et al. (2019a), given as:

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

$$ECT_{it} = y_{it-1} - X_{it}\theta \quad (4)$$

In both equations (3) and (4), y stands for the explained variable (i.e. LCO2), 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 all the individual 10 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 tests 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 all 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 carbon dioxide emission while Israel records the lowest average value. 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 has the highest average value of 8.81, while economic policy uncertainty has a negative average value of 2.94. Except for carbon dioxide emission and energy consumption that exhibit higher mean dispersion of 1.24 and 1.20, respectively, other variables show lower variability. Expectedly, the real gross domestic product has the highest maximum value, while economic policy uncertainty recorded the lowest minimum value.

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

3.1 Pesaran's Test of Cross-Sectional Independence

Cross-sectional dependence (CD) test is a very important pre-test that must be conducted in every panel data analysis. This 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 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.		

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 geopolitical risk is insignificantly related to CO_2 emission. It can be seen that economic growth and policy uncertainty have a significant negative relationship with carbon dioxide emission. Additionally, a thorough inspection of the relationship among the independent variables reveals the absence of multicollinearity problem. This is because the correlation coefficients are below 0.80, which is a rule of thumb.

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					

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 reveal that energy consumption, carbon dioxide and economic growth are integrated at first difference while geopolitical risks and economic policy uncertainty are stationary at levels.

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.				

Having established the order of stationarity, Pedroni cointegration test is utilized to validate if the variables for cointegration. The p-value of the Kao cointegration t-static is less than 5%. This authenticates the result of the Pedroni cointegration test.

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, 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.		

3.4 Results of PMG-ARDL

The study reports results of PMG-ARDL, although results of MG-ARDL was also carried out with Hausman test to decide on which model to adopt. The choice of PMG is reasonable since it assumes the long-run slope coefficient to be identical and allows for other coefficient to differ across sections as against MG-ARDL (See appendix for the results) which accounts for heterogeneity in all coefficient (Pesaran and Smith, 1995). The results of the PMG-ARDL (1,1,1,1,1) for the three models provided in Table 7 are similar for the error correction term in terms of significance, size and sign. The values of the error correction term 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 model respectively diverge rather than converge to the long-run equilibrium.

The first model displays 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 & Nsiah (2019) and Adams & Klobodu (2018) in Sub-Saharan African countries and selected African countries respectively 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. This suggests 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, though it significantly decreases CO_2 emission by 0.02% in the long-run which is less than the 0.03% damage done to the environment the short-run. This finding lends credence to Waqih et al.

(2019), who reported a significant negative relationship between the square of economic growth and CO_2 emission in SAARC region. Furthermore, 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 carbon dioxide emission increases significantly by 1% for every 1% increase in energy consumption both in the short- and long-run, *ceteris paribus*. 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

Table 7. 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.					

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. Specifically, the work of Acheampong et al. (2019) for 46 sub-Saharan African countries. Geopolitical risk exerts no significant effect on carbon dioxide emission in the short run. However, the level of geopolitical risk has a significantly negative impact on environmental quality in the long run. Specifically, a 1% increase in geopolitical risks reduces environmental degradation by 0.035%. The implication of this result is that political instability in the resources-rich countries will reduce environmental degradation. This contrasts the *apriori* expectation, but could be explained by the fact that political instability distorts exploration, production, and consumption of of energy resources, which could lead to reduction in carbon dioxide emissions.

Economic policy uncertainty increases emissions of CO_2 by 0.002% and 0.012% in the short- and long-run respectively, *ceteris paribus*. This is not unexpected as firms' cash-flow, cash-holding and external financing have been proven to be negatively affected by economic policy uncertainty which in turn lower energy efficiency innovation and increase the level of carbon emission. It is worthy of note that even though economic policy uncertainty induces carbon dioxide emission, the effect on CO_2 emission is far less than the effect of energy consumption on CO_2 emission. In other words, economic policy uncertainty triggers a slight increase in carbon dioxide emission in resource-rich but crisis-prone economies.

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 effect positively 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 can address the problem of environmental degradation by formulating policies that promote efficient use of carbon emission materials during the production processes. Like the first model, the second model reveals the existence of Environmental Kuznets Curve in the long-run while the short-run result suggests an inverted U-shape relationship among the variables.

Energy consumption is positive and significant at 1% in the short- and long-run. So, an additional 1% 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. This suggests that higher energy consumption adversely affected environmental quality in the resource-rich but crisis-prone economies. 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. Furthermore, 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. This clearly shows that exclusion of geopolitical risk from the model does not aggravate the impact of uncertainty in policy on carbon emission.

The result of the third model reveals that economic growth insignificantly increases rather than decreasing carbon emission in the short- and long-run. This finding slightly contrasts the results of the first and second model, which depicts that growth and carbon emission in the short run a negatively related. The square of economic growth enhances environmental quality in the short- and long-run. There is also a slight difference between this finding and the previous models, which indicate a positive relationship between the square of economic activities and carbon emission in the short 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 and GPR with energy consumption in the selected countries. The results are not different from the earlier findings suggesting that the results are robust.

3.5 Dumitrescu and Hurlin Panel Causality

The Dumitrescu and Hurlin (2012) panel causality result presented in Table 8 suggest 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 each group of the variables. The feedback relationship between energy consumed and CO_2 emission support 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 consumed and CO_2 emission. Belaïd and Zrelli (2019) and Khan et al (2019) also reported a feedback relationship between energy consumed and CO_2 emission for nine Mediterranean Countries and 193 Countries respectively.

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

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

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

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 flowing from 1) carbon emissions to geopolitical risk 2) economic 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. No evidence of causality is found between economic policy uncertainty (EPU) and geopolitical risk (GPR). This implies that policy uncertainty has no effect whatsoever on the geopolitical risk.

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 the Panel Pooled Mean Group-Autoregressive Auto regressive distributed lag model (PMG-ARDL) suggest that energy consumption and economic growth trigger carbon emissions. Additionally, there is a significant association between economic uncertainties and CO_2 emissions in the long-run, while this relationship is negative for geopolitical risks. 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 still record high economic growth. The cointegration tests reveal 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 carbon dioxide 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 development to promote the necessary technologies for the development and design of more efficient energy systems to reduce environmental pollution and ensure that growth does not occur at the expense of the environment.

Second, economic policy uncertainty aggravates carbon dioxide emission 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 most notably in the short-run because geopolitical risks have an adverse effect on CO_{2s} emission in the short-run.

Third, related to the second point is the principle that policy makers are plagued by uncertainty in such a process, which makes it difficult for them to come up workable solutions. Thus, ignoring uncertainty could lead to mis-specification or quantification of the energy consumption –carbon dioxide 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., 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, consistent with Contreras and Platania (2019) and Workman et al.'s (2020) studies, 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 and avoid flawed environmental policy advice.

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Appendix

A. 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

Table A1. 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.