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IS THERE ANY RELATIONSHIP BETWEEN GEOPOLITICAL RISK AND CLIMATE CHANGE?

Abstract

Purpose: The aim of this study is to point out the impact of geopolitical risk on climate change. The CO_2 emissions per capita is used as a proxy for climate change.

Methodology: In this study, the data sample covers annual data from 1990 to 2015 for 12 selected Latin American and Asian countries. After standard preliminary tests (Cross-sectional dependence tests, CIPS unit root test, and slope homogeneity test), we employ the second-generation estimator – the AMG (Augmented Mean Group) method to explore the long-run relationship between geopolitical risk and CO_2 emissions per capita.

Results: The AMG findings document that a 1% rise in geopolitical risk escalates CO_2 emissions per capita by 0.001%. In addition, economic growth and fossil energy consumption foster CO_2 emissions per capita, whereas renewable energy contributes to decreasing CO_2 emissions per capita.

Conclusion: In recent years, scholars have attempted to explore the impact of geopolitical risk on environmental degradation. According to our results, in Latin American and Asian countries, decreasing geopolitical risk and conflict can impede environmental degradation. In the long run, a robust clean energy policy should be considered in case of geopolitical conflict by the government. Besides, the government should focus on renewable energy policy and substitute non-renewable energy resources with more technology-intensive resources.

Keywords: Geopolitical risk, climate change, environmental degradation, CO_2 emissions

1. Introduction

Climate change is one of the most critical global issues of today. The increase in energy use with the development of economic and commercial activities is the leading cause of climate change. Global energy demand is increasing due to economic growth and population growth. If alternative renewable energy sources do not substitute primary energy demand, it will contribute to global climate change. In addition, the gradual increase in energy consumption complicates the fight against climate change (Our World in Data, 2021a). According to the IEA (2019) report, global energy demand increased by 2.3% in 2018. This increase represents the highest level since 2010. While the share of fossil fuels was 80% as of 2000, if this trend continues, the share of fossil fuels is expected to decrease to

74% with little change in 2030 within the framework of sustainable development goals.

CO_2 emissions, which have a significant share in greenhouse gas emissions, are among the most important causes of global climate change. Approximately 76% of the total greenhouse gas emissions belong to CO_2 emissions (Center for Climate and Energy Solutions, 2021). Greenhouse gas emissions are also closely related to global warming. The global temperature increased by an average of 1.1°C in 2020 compared to 1850 (Our World in Data, 2021b).

IPCC (2018) proves the noticeable assessment for the future in its well-known report.

"Human activities are estimated to have caused approximately 1.0°C of global warming above pre-industrial levels, with a likely range of 0.8°C to 1.2°C. Global warming is likely to reach 1.5°C between 2030 and 2052 if it continues to increase at the current rate. (high confidence)."

In this context, substantial literature exists about the driver of CO_2 emissions, one of the virtual drives of climate change. Moreover, the related literature investigates different factors as determinants of CO_2 emissions, for example, economic growth, energy consumption, foreign direct investment, foreign trade, and renewable energy. In addition to the factors mentioned above, some studies (Adams et al., 2020; Akadiri et al., 2020; Hashmi et al., 2021; Zhao et al., 2021; Anser et al., 2021a, 2021b) that examine the impacts of geopolitical conflicts on climate change have recently come to the fore. Namely, geopolitical risk (GPR) is another dimension of climate change.

Geopolitical risk is increasing day by day. Developments such as conflicts among countries, terrorist attacks, and bomb attacks have an economic, political, social, and environmental impact (Caldara & Iacoviello, 2018; Anser et al., 2021a; Hashmi et al., 2021). Theoretical discussions explain the impact of geopolitical risk on the environment with two opposite approaches. From an optimistic perspective, GPR causes a decrease in economic activity and energy consumption. Thus it negatively affects environmental degradation. In contrast, according to the pessimistic view, GPR diminishes the research and development (R&D) process, discourages innovation policy, and hinders renewable energy investment. So it promotes to raise environmental degradation (Anser et al., 2021b).

In sum, the nexus between geopolitical risk and environmental degradation is not clear. Based on theoretical debates, there is a need for more empirical findings to clarify the relationship between geopolitical risk and environmental degradation. Hence, our study intends to explore the linkage between geopolitical risk and CO_2 emissions in selected Latin American and Asian countries: Mexico, Korea, India, Brazil, China, Indonesia, Argentina, Colombia, Venezuela, Thailand, Malaysia, and the Philippines for the period 1990-2015.

We have selected the Latin American and Asian countries in our analysis for the following reasons: (i) Latin American and Asian countries consume approximately 41.8% of global primary energy; ii) They emit about 47% of global CO_2 emissions; and iii) These countries have higher geopolitical risks, and there are many geopolitical tensions and conflicts in their region.

Our paper contributes to the existing literature in three ways. (i) To the best our knowledge, this is the first analysis to investigate the relationship between geopolitical risk and climate change for 12 Latin American and Asian countries. (ii) Political instability, terrorism, and conflicts are mainly considered risk indicators in the extant literature (Lu et al., 2020). However, we use the geopolitical risk (GPR) index as an indicator of geopolitical risks that consists of comprehensive combinations. (iii) We employ second-generation panel estimators considering cross-sectional dependency and slope homogeneity to explore the long-run relationship among variables.

The rest of this study is organized as follows: Section 2 presents the literature review; Section 3 provides the data, model, and methodology; findings are presented in Section 4, and discussion and policy recommendations based on results are put forward in Section 5.

2. Relevant literature

We categorized the empirical literature into three groups. The first group of studies examines the main driving factor of CO_2 emissions in selected countries. The second group of studies examines the relationship between geopolitical risk and economic performance. The last group investigates the dynamic linkage between geopolitical risk and environmental degradation. Table 1 offers the literature review of the issue.

Table 1 Summary of relevant literature

Study	Sample/ Period	Variables	Method	Finding(s)
Determinants of CO_2 emissions in selected countries				
Lee & Yoo (2016)	Mexico/ 1971 - 2007	Energy consumption (EC), CO_2 emissions (CO_2), real GDP (GDP)	Unit root, co-integration, and the error-correction model (ECM)	A one-way causality real GDP → EC, CO_2 → real GDP; two-way causality EC ↔ CO_2
Sasana & Putri (2018)	1990-2014/ Indonesia	CO_2 emissions (CO_2), population growth (POP), fossil energy (FOS), renewable energy (REN)	Ordinary Least Square (OLS)	FOS and POP positively affect CO_2; REN negatively affects CO_2
Jardón et al. (2017)	1971-2011/20 Latin American and Caribbean countries	CO_2 emissions per-capita (CO_2), real GDP per capita (GDP)	Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS)	EKC hypothesis is valid
Hanif et al. (2019)	1990-2013/ Emerging Asian economies	CO_2 emissions per-capita (CO_2), real GDP per capita (GDP), fossil fuels consumption (FFC), foreign direct investment (FDI), population growth (POP)	Panel Autoregressive Distributed Lags (ARDL)	GDP, FFC, and FDI have a positive impact on CO_2
Eriandani et al. (2020)	1980-2018/ASEAN countries	CO_2 per capita (CO_2), foreign direct investment (FDI), GDP per capita (GDP), manufacturing value-added (MAN)	Granger causality	A one-way causality FDI → CO_2
Relationship between geopolitical risk and economic indicator				
Soltani et al. (2021)	1995-2020/15 MENA countries	GDP per capita (GDP), foreign direct investment (FDI), financial development (FD), inflation (INF), trade openness (OPNS) geopolitical risk index (GPR)	Panel Vector Auto-Regression (PVAR)	GPR negatively affects GDP, whereas FD affects GDP in some countries
Soybilgen et al. (2019)	1986-2016/18 emerging nations	Real GDP growth rate (GDP), geopolitical risk index (GPR), human capital (HC), investment expenditure (INV), government expenditure (GOV), trade openness (TRADE)	Fixed effect	GDP harms real GDP
Lee et al. (2021)	2005M1-2017M12/ Selected 16 countries	Tourism demand (Q), per capita income (Y), relative prices (P), Inbound tourists (IT), Exchange rate (EX), Geopolitical risk (GPR)	AMG and Common Correlated Effects Mean Group (CCEMG)	GDP impedes Q
Le & Tran (2021)	1995-2018/9 Asian countries	Geopolitical risk index (GPR), capital expenditures (CAPX/ ASSET), rule of law, investment freedom, GDP growth, inflation	Fixed effect, Two-Stage Least-Squares (2SLS), Generalized Method of Moments (GMM)	GPR strongly affects institutional investment in China and Russia, while small in India and Turkey

Study	Sample/ Period	Variables	Method	Finding(s)
Hailemariam & Ivanovski (2021)	January 1999-August 2020/U.S.	Geopolitical risk index (GPR), world industrial production (WIP), price level (P), net expenditure for tourism exports and imports (TNX)	Structural Vector Autoregression (SVAR)	GPR negative affects TNX
Alsagr & Almazor (2020)	1998-2017/ Emerging nations	Return on assets, Geopolitical risk index (GPR), oil rents, inflation, GDP, exchange rate, Non-performing loan, Bank deposits	Fixed effect	GPR plunges banking sector performance
Bilgin et al. (2020)	1985-2015/18 countries	Government investments (GI), geopolitical risk (GPR), per capita GDP (GDP), population (POP), trade openness (TO), age dependency (AD), urban population (UP), capital formation (CF), FDI, total debt (TD), budget deficit (BD)	Fixed-effects, Least Squares Dummy Variable Corrected (LSDVC)	GPR incentives GI
Olanipekun & Alola (2020)	1975-2018/ Persian Gulf	Oil production (PROD), geopolitical risk index (GPR), natural resources rents (RENT), average damage cost (ACOD), crude oil price (PRICE)	Non-Linear Autoregressive Distributed Lag (NARDL)	Positive shocks in GPR and ACOD negatively affect PROD whereas negative shock in PRICE exerts PROD negatively
Akadiri et al. (2020)	1985Q1-2017Q4/Turkey	Geopolitical risk index (GPR), real GDP (GDP), number of inbound tourists (TOUR)	Toda & Yamamoto causality test (1995)	GPR negatively affects real GDP and TOUR; also a one-way causality GPR → GDP, GPR → TOUR
Geopolitical risk and environmental degradation				
Anser et al. (2021a)	1985-2015/ BRIC	Geopolitical risk index (GPR), carbon dioxide emissions (CO_2), GDP per capita (GDP), non-renewable energy (ENE), renewable energy (REN), total population (POP)	AMG	GPR, GDP, POP, and ENE increase CO_2 while REN impedes CO_2
Anser et al. (2021b)	1995-2015/ Brazil, Mexico, Russia, Colombia, and China	Ecological footprint (EF), GDP per capita (GDP), non-renewable energy (EN), renewable energy (REN), economic policy uncertainty index (EPU), geopolitical risk index (GPR)	Co-integration, FMOLS, DOLS, AMG	EPU and EN foster EF while GPR and GDP decrease EF
Zhao et al. (2021)	1985-2019/ BRIC	Carbon dioxide emissions (CO_2), energy consumption (EC), geopolitical risk index (GPR), government stability (GS), GDP per capita (GDP)	NARDL	An increase in GPR plunges CO_2 in Russia and South Africa; a decrease in GPR decreases CO_2 in India, China, and South Africa
Hashmi et al. (2021)	1970-2015/ Global Level	World carbon dioxide emissions (CO_2), geopolitical risk index (GPR), world GDP (GGDP), world energy consumption (GEN)	Bootstrap ARDL	EKC is valid; GPR negatively affects CO2 in the short run, positively affects in the long run

Study	Sample/ Period	Variables	Method	Finding(s)
Sweidan (2021)	1973Q1-2020Q1/U.S.	Geopolitical risk index (GPR), world oil prices (OP), real gross domestic product (Y), renewable energy (RER), real economic growth (GW) and long-run economic growth (LGW)	ARDL	GPR positively affects RER
Adams et al. (2020)	1996-2017/ Resource-rich countries	CO_2 emissions (CO_2), real GDP per capita (RGDP), energy use (ENC), economic policy uncertainty (EPU), geopolitical risk index (GPR)	PMG-ARDL, Kao cointegration, Dumitrescu and Hurlin (2012) causality test	ENC and RGDP increase CO_2; a bidirectional causality $CO_2 \leftrightarrow$ ENC, RGD $\leftrightarrow$ PEPU, RGDP $\leftrightarrow CO_2$; a unidirectional causality $CO_2 \rightarrow$ GPR
Alsagr & Hemmen (2021)	1996-2015/ Developing countries	Renewable energy (REC), private credit (PCD), bank credit (BCB), domestic credit (DCP), stock market turnover ratio (TOR), geopolitical risk index consumer price index (CPI), GDP per capita (GDPPC)	Two-step system GMM	Financial development and GPR cause an increase in REC
Rasoulinezhad et al. (2020)	1993-2018/ Russia	Energy transition (ET), inflation (INF), CO_2 emissions (CO_2), exchange rate (EXC), economic growth (GRO), population (POP), financial openness (FIN), geopolitical risk (GEO)	ARDL Bounds Testing	GEO positively affects ET

Source: Authors

After examining the related literature, it is seen that the empirical literature about the relationship between geopolitical risk and climate change is quite scarce. This refers especially to the effect of geopolitical risk on environmental degradation for Latin American and Asian countries, many of which have substantial geopolitical disputes and conflicts on a regional and global scale, for which previous research does not offer extensive empirical evidence.

3. Data and method

3.1 Data

Our paper aims to investigate the impact of geopolitical risk on climate change by using the annual panel data of 12 Latin American and Asian countries (Mexico, Korea, India, Brazil, China, Indonesia, Argentina, Colombia, Venezuela, Thailand, Malaysia, and the Philippines) spanning the period 1990-2015. Data on the GPR index, developed by Caldara and Iacoviello (2018), are extracted from http://policyuncertainty.com and then converted into annual data. The GPR index is calculated via the frequency of newspaper articles involving notions related to geopolitical tension and conflict.

The dependent variable is CO_2 emissions as a proxy for climate change, whereas the control variables are GDP per capita (GDP), total population (POP), fossil energy consumption (FEUSE), and renewable energy consumption (REN), respectively. Annual data for control variables are gathered from World Bank. Table 2 provides the description, scope, and sources of variables.

Table 2 Summary of variables

Variable name	Abbreviation	Scale	Source
Carbon dioxide emissions	CO_2	Metric ton per capita	World Bank
GDP per capita	GDP	GDP per capita (constant 2010 $ US)	World Bank
Population	POP	Total population	World Bank
Fossil energy consumption	FEUSE	Percent of total final energy	World Bank
Renewable energy consumption	REN	Percent of total final energy	World Bank
Geopolitical risk index	GPR	Tally of newspaper articles containing geopolitics related terms	http://policyuncertainty.com

Source: Authors

3.2 Method

This paper explores the long-term relationship between geopolitical risk and climate change. The impacts of the population (P), welfare (A), and technology (T) on environmental degradation were firstly discussed within the framework of the IPAT (Environmental Impact by Population, Affluence, and Technology) model developed by Ehrlich and Holdren (1971). The classical form of the IPAT model is given as follows:

$$I = P.A.T\ (I = PAT) \tag{1}$$

In Eq. (1), I denotes influence (environmental degradation), P is population, A represents affluence or economic development, and T is technology. However, this model cannot fully reveal the effects of external variables that impact the environment individually, handles anthropogenic effects in a limited way, and is based on a simple equation that equally determines the impact of all variables on the environment (Wang et al., 2016, p. 1184). To overcome the limitations of the IPAT model, the STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model was developed by Dietz and Rosa (1997). The general form of the STIRPAT model is as follows:

$$I_i = aP_i^b A_i^c T_i^d e_i \tag{2}$$

Eq. (2) keeps the general properties of the IPAT model; I, A, and P denote (environmental degradation), affluence or economic development, and population, respectively, as shown in Eq. (1). But, the "i" subscript is added to the STIRPAT model to emphasize that these quantities vary according to the observation units. In Eq. (2), The terms b, c, and d, which express the coefficients of the explanatory variables, are estimated by applying standard statistical techniques. Namely, a denotes the constant term, while b, c, and d are the elasticities that determine the net impact of population welfare and technological changes on the environmental effects, respectively. In the STIRPAT model, the term T (technology) represents technological development and includes all other factors that reveal the impact of social organizations, institutions, culture, and individuals on the environment (Dietz & Rosa, 1997, p. 175). Anser (2019), Destek (2018), and Shahbaz et al. (2016) show in their study that the advantage of the STIRPAT model allows to include related variables in terms of analysis. Thus, we can add the geopolitical risk index into the model based on Anser et al.'s (2021a) study.

The new extended form of STIRPAT is as follows:

$$I_{it} = aP_{it}^b A_{it}^c T_{it}^d G_{it}^f e_{it} \tag{3}$$

In Eq. (3), G denotes the geopolitical risk index (GPR). All variables are converted to a logarithmic form to escape the heterogeneity problem. So the new form of the model can be expressed as follows:

$$\begin{aligned} logI_{it} = a + b(logP_{it}) + c(logA_{it}) \\ + d(logT_{it}) + f(logG_{it}) + e_{it} \end{aligned} \tag{4}$$

Where a is the intercept; b, c, d, and f are coefficients, with i and t representing cross-section and time, respectively, and e_{it} is the error term. The final empirical model used yields:

$$\begin{aligned} log(CO_{2,it}) = a + \beta_1 \log(GDP_{it}) + \beta_2 \log(POP_{it}) \\ + \beta_3 \log(FEUSE_{it}) + \beta_4 \log(REN_{it}) \\ + \beta_5 \log(GPR_{it}) + e_{it} \end{aligned} \tag{5}$$

In Eq. (5), $CO_{2,it}$ is carbon dioxide emissions per capita, GDP_{it} is GDP per capita, used as a proxy for A (affluence). $FEUSE_{it}$ represents fossil energy consumption for non-renewable energy consumption and REN_{it} denotes renewable energy consumption. Both $FEUSE_{it}$ and REN_{it} are utilized as proxies for T (technology). POP_{it} represents total population, GPR_{it} is the geopolitical risk index, and α_i stands for country fixed effects.

Several empirical pieces of evidence (Chen & Huang, 2013; Mesagan, 2015; Uddin & Wadud, 2014; Zhang et al., 2021) show that economic growth positively impacts CO_2 emissions. Non-renewable energy is also one of the critical determinants of CO_2 emissions, and it is positively associated with CO_2 emissions; in contrast, renewable energy has a negative impact on CO_2 emissions (Chen & Geng, 2017; Sharif et al., 2019; Fatima et al., 2021). Furthermore, the relationship between population and CO_2 emissions is unclear (Zhou & Liu, 2016; Zhang et al., 2018; Khan & Yahong, 2021). Recently, a few studies have considered geopolitical risk as a new determinant of environmental degradation (Anser et al., 2021a; Anser et al., 2021b; Zhao et al., 2021).

3.2.1 Cross-sectional dependence

In empirical analyses, cross-sectional dependence (CD) is one of the critical points to obtain robust results. Ignoring CD may lead to inconsistent results. In this framework, before testing stationarity properties of variables, we employ Breusch-Pagan LM, LM_{adj}, and Pesaran CD tests for testing cross-sectional dependence among variables. Breusch-Pagan LM test provides consistent and reliable results in case of relatively small cross-section (N) and sufficiently large time dimension (T), and can be reported as follows (Huang, 2016, p. 253):

$$LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2 \tag{6}$$

In Eq. (6), i indices denote cross-section and T is time.

The Pesaran CD test can be expressed as follows:

$$CD = \sqrt{\left(\frac{2T}{N(N-1)}\right)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(\hat{\rho}_{ij}-1\right)\sim N(0,1) \tag{7}$$

In the Pesaran (2004) CD test, under the null hypothesis of no cross-sectional dependence with $T\rightarrow\infty$ and $N\rightarrow\infty$, this test statistic is asymptotically distributed as standard normal. However, in some cases, due to the decreasing power of the Pesaran (2004) CD test (Chang et al., 2015a, p. 291) the revised version of the LM test, the bias-adjusted LM, proposed by Pesaran et al. (2008), can be used where N is large, and T is small. The bias-adjusted LM statistic is defined as follows (Pesaran et al., 2008, p. 108; Chang et al., 2015b, p. 1407):

$$LM_{adj} = \sqrt{\left(\frac{2T}{N(N-1)}\right)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\frac{(T-k)\hat{\rho}_{ij}^2-\mu_{Tij}}{\sqrt{v_{Tij}^2}}\sim N(0,1) \tag{8}$$

In Eq. (8), μ_{Tij} and v_{Tij}^2 denote the mean and variance of $(T-k)\hat{\rho}_{ij}^2$, respectively.

3.2.2 Slope homogeneity

Testing slope homogeneity is another critical preliminary stage in panel data econometrics. This study employs the Delta ($\tilde{\Delta}$) test proposed by Pesaran & Yamagata (2008). Under the null hypothesis of slope parameters are homogenous, the slope homogeneity test of Pesaran & Yamagata (2008) can be written as follows:

$$\tilde{S} = \sum_{i=1}^{N}\left(\hat{\beta}_i-\tilde{\beta}_{WFE}\right)'\frac{x_i'M_\tau x_i}{\tilde{\sigma}_i^2}\left(\hat{\beta}_i-\tilde{\beta}_{WFE}\right) \tag{9}$$

In Eq. (9), $\hat{\beta}_i$ is the pooled ordinary least squares (OLS) estimator whereas $\tilde{\beta}_{WFE}$ is the weighted fixed effect pooled estimator, $\tilde{\sigma}_i^2$ is the estimator of σ_i^2, and M_τ is a matrix of T (Pesaran & Yamagata, 2008, p. 54).

3.2.3 Panel unit root

Various panel unit root tests exist that determine the stationary properties of variables. However, the first-generation panel unit root tests do not allow cross-sectional dependence. So in the presence of cross-sectional dependence, the first-generation panel unit root tests do not provide reliable results (Anser et al., 2021a). In this study, we perform the CIPS unit root test, which is one of the second-generation panel unit root tests that consider the presence of cross-sectional dependency heterogeneity (Rath & Akram, 2021).

The CIPS test is a derivative of the CADF (Cross-Sectional Augmented Dickey-Fuller) test developed by Pesaran (2007). The CADF regression is (Pesaran, 2007, p. 269):

$$\Delta Y_{it} = \alpha_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \varepsilon_{it} \quad (10)$$

Where α_i is deterministic trend, $\bar{Y}_t = \frac{1}{N}\sum_{i=1}^{N} Y_{it}$ and $\Delta\bar{Y}_t = \frac{1}{N}\sum_{i=1}^{N} \Delta Y_{it}$ (Wang et al., 2020).

After running the CADF statistics, the CIPS statistic, which is the mean of the CADF statistics, is calculated as follows:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} \tilde{t}_i \quad (11)$$

Where $\tilde{t}_i$ represents the OLS t ratio of b_i. The critical values are obtained from Pesaran's (2007) study for testing unit root in all variables (Rodríguez & Valdés, 2019).

3.2.4 Augmented Mean Group (AMG) estimator

The last step of our empirical analysis is to estimate the regression equation (5). The current study estimates the long-run relationship between geopolitical risk and CO_2 emissions using the AMG estimator proposed by Eberhardt and Bond (2009) and Bond and Eberhardt (2013). The AMG estimator is robust across heterogeneity and cross-sectional dependence. Furthermore, the AMG estimator allows estimating of the model with non-stationary variables. In other words, the AMG method does not require the stationarity condition of the series (Destek, 2017), and it contains a two-step stage (Eberhardt & Bond, 2009).

The first stage of the AMG method can be written as follows

$$\Delta y_{it} = b'\Delta x_{it} + \sum_{t=2}^{T} c_t \Delta D_t + e_{it} \quad \Rightarrow \hat{c}_t \equiv \hat{\mu}_t^{\bullet} \quad (12)$$

Then, the second stage of the AMG method yields:

$$y_{it} = a_i + b_i' x_{it} + c_i t + d_i \hat{\mu}_t^{\bullet} + e_{it} \quad \Rightarrow \hat{b}_{AMG} = N^{-1}\sum_i \hat{b}_i \quad (13)$$

Eq. (12) refers to the ordinary least squares (OLS) regression, where ΔD_t illustrates T-1 period dummies in first differences, $\hat{\mu}_t^{\bullet}$ labels year dummy coefficients. In Eq. (13) $\hat{\mu}_t^{\bullet}$ represents the N group-specific regression whereas $\hat{\beta}_i$ shows the mean of the individual coefficient estimates, following the Pesaran and Smith (1995) mean-group approach (Bond & Eberhardt, 2013).

4. Empirical results

In the first stage of the empirical analysis, we investigate the cross-sectional dependence. The results are provided in Table 3.

Table 3 Cross-sectional dependence tests results

	$LnCO_2$	LnGDP	LnFUSE	lnREN	LnPOP	LnGPR
LM	728.8 [0.000]	285.7 [0.000]	311.8 [0.000]	279.7 [0.000]	270.8 [0.000]	696.9 [0.000]
CD_{LM}	22.82 [0.000]	5.285 [0.000]	8.963 [0.000]	8.393 [0.000]	4.296 [0.000]	22.27 [0.000]
CD	28.499 [0.000]	40.046 [0.000]	11.184 [0.000]	9.943 [0.000]	41.301 [0.000]	14.71 [0.000]
La_{mada}	163.2 [0.000]	50.19 [0.000]	59.47 [0.000]	51.8 [0.000]	48.31 [0.000]	155.3 [0.000]

Homogeneity Test	Test Statistics	Probability
$\tilde{\Delta}$	14.458	0.000
$\tilde{\Delta}_{adj}$	17.030	0.000

Source: Authors

The results show that the null hypothesis of no cross-sectional dependence is rejected at 1%. These results show dependence between countries in economic, political, and social fields; in other words, a shock in one country can affect another country. Similarly, the slope homogeneity test results show that the null hypothesis of slope parameters are homogeneous and is rejected at 1%. Given the presence of cross-sectional dependence and slope heterogeneity, the first-generation unit root tests results can be biased and unreliable. Thus we employ the CIPS unit root test that allows the investigation of the stationary properties of variables. The CIPS unit test results are reported in Table 4.

Table 4 The results of the CIPS unit root test

Variables	I(0)	I(1)
$LnCO_2$	-1.612	-4.409***
LnGDP	-1.862	-3.976***
LnFEUSE	-2.057	-4.841***
LnREN	-1.810	-4.229***
LnPOP	-1.718	-2.185**
LnGPR	-2.370***	-

Note: *** and ** denote significance at 1% and 5%, respectively. The critical value at 1% is (-2.34), 5% (-2.17) and 10% (-2.07), respectively.

Source: Authors

As can be seen from Table 4, the null hypothesis of a unit root can be rejected at I(0) only for the GPR index. However, the null hypothesis of a unit root can be rejected at I(1) for CO_2, GDP, FEUSE, REN, and POP, respectively. Thus, it can be said that the variables are stationary at different levels.

This paper employs the AMG method to determine the long-term relationship between the variables since the series have cross-sectional dependence and stationarity at different levels (Destek, 2020). In this regard, Table 5 reports the AMG results.

Table 5 AMG results

Dependent Variable	LnGDP	LnFEUSE	LnREN	LnPOP	LnGPR
$LnCO_2$	0.556***	0.784**	-0.009***	-9.008	0.001**

Note: ***and ** imply significance at 1% and 5%, respectively.

Source: Authors

The AMG results show that GDP, FEUSE, and GPR positively impact CO_2 emissions while REN is negatively associated with CO_2 emissions. The coefficient of geopolitical risk is positive and statistically significant, implying that an increase of 1% in geopolitical risk escalates the CO_2 emissions per capita by 0.001%. This finding is in line with the studies of Anser et al. (2021a), Hashmi et al. (2021), and Bildirici & Gokmenoglu (2020).

5. *Conclusion and policy recommendations*

In the 21st century, geopolitical risks and debates are increasing worldwide. Although the geopolitical risk significantly affects economic growth, investments, and many macroeconomic indicators; its impact on climate change and environmental degradation is not clear enough. Based on this framework, this study aims to analyse the impact of geopolitical risk, economic growth, fossil energy use, renewable energy consumption, and total population on CO_2 emissions in selected Latin American and Asian countries over the period from 1990 to 2015. The findings from the AMG method confirm that geopolitical risk fosters CO_2 emissions. Furthermore, economic growth and fossil energy use lead to rising CO_2 emissions. As opposed to that, renewable energy consumption is negatively associated with CO_2 emissions.

These countries are exposed to high geopolitical risks. The increase in geopolitical risks increases militarization activities, adversely affecting the environment (Bildirici, 2017). Because within militarization, the use of military equipment and routine military activities require a high amount of energy consumption (Solarin et al., 2018). Building large-scale military infrastructure in terms of national security concerns accelerates environmental deterioration (Clark & Jorgenson, 2012). The impact of economic growth on environment degradation is positive, as expected. In other words, as economic growth increases, environmental degradation increases as well. This outcome is consistent with many studies in the existing literature (Bouznit & Pablo-Romero, 2016; Alam, 2014; Hanif et al., 2019; Nosheen et al., 2021; Koengkan & Fuinhas, 2020). One of the most important reasons for this is that the economic structure heavily depends on the primary sector that requires more energy consumption in these countries. Since economic growth requires high levels of fossil energy, particularly in developing countries, it triggers environmental degradation and climate change (Ali et al., 2021; Li & Yang, 2016; Liu et al., 2020). Also, renewable energy is negatively associated with climate change in these countries. However, a well-designed renewable energy system contributes to energy efficiency and decreases dependency on fossil energy, reducing the climate change process (Sahoo & Sahoo, 2020; Haldar & Sethi, 2021).

Based on the above findings, we put forward some policy recommendations. First, policy-makers should strive to decrease geopolitical risks and tensions between countries. In this regard, the agreements and treaties have critical roles among nations. Moreover, non-governmental organizations (NGOs) undertake to plunge into geopolitical risks in this process. Secondly, governments expand incentives for renewable energy and tighten the non-renewable energy policy. Latin American and Asian economies still depend on primary energy sources such as fossil energy. Therefore, energy transition should become one of the most preliminary agendas in these countries.

The main limitation of our paper is that we analyse the impact of geopolitical risk on climate change by controlling economic growth, population, fossil energy, and renewable energy consumption. However, various factors affect climate change via interaction with geopolitical risk. For instance, nowadays, institutional quality and globalization are closely related to geopolitical risks. Thus, future studies can focus on the impact of these factors on different countries.

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