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Research article

The impact of geopolitical risk on CO_2 emissions inequality: Evidence from 38 developed and developing economies

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ABSTRACT

This paper analyses the impact of geopolitical risk on carbon dioxide (CO_2) emissions inequality in the panel dataset of 38 developed and developing economies from 1990 to 2019. At this juncture, the empirical models control for the effects of globalisation, capital-labour ratio, and per capita income on CO_2 emissions inequality. The panel cointegration tests show a significant long-run relationship among the related variables in the empirical models. The panel data regression estimations indicate that geopolitical risk, capital-labour ratio, and per capita income increase CO_2 emissions inequality. However, globalisation negatively affects CO_2 emissions inequality in the panel dataset of 38 developed and developing countries. The pairwise panel heterogeneous causality test results align with these benchmark results and indicate no reverse causality issue. Potential policy implications are also discussed.

1. Introduction

Climate change is one of today's most pressing issues (Dow and Downing, 2016). The average global temperature is expected to rise by 3–5 °C by 2100, which could have devastating consequences for the planet (Hansen et al., 2006). The leading cause of climate change is the emissions of greenhouse gases, such as CO_2 emissions (Nordhaus, 2018). These gases trap heat in the atmosphere, which causes the planet to warm (May and Kidder, 2022). The main reason for the increase in CO_2 emissions is the consumption of fossil fuels (Lin and Xu, 2020). When fossil fuels are burned, they release CO_2 into the atmosphere (Adebayo et al., 2023). This is why reducing our reliance on fossil fuels and transitioning to cleaner energy sources is vital (Gozgor and Paramati, 2022). Therefore, the primary goal should be to reduce CO_2 emissions to combat the adverse effects of climate change and global warming (Syed and Bouri, 2022). Overall, understanding the factors contributing to CO_2 emissions is essential for policymakers to develop effective strategies to mitigate climate change.

The factors influencing CO_2 emissions are complex and can vary from country to country. It is essential to analyse the drivers of CO_2 emissions across countries because each economy has a different level of economic development and various cultural, economic, political, and social factors. Countries' sensitivity to environmental degradation also differs, and governments can implement different environmental policies (see, e.g., Chen et al., 2020; Fang et al., 2021; Fu et al., 2021; Gozgor et al., 2019; Lau et al., 2023; Li et al., 2021; Mardani et al., 2019; Sarker et al., 2023; Sun and Huang, 2020; Xie et al., 2021; Yu et al., 2023; Zhang et al., 2022; Zheng et al., 2019).

Previous empirical papers have focused on the total amount of CO_2 emissions, but this paper considers a new indicator: CO_2 emissions inequality. This measure is calculated by considering people's total (personal) per capita carbon footprint within a country's top 10% income threshold (Chancel, 2022). According to the data, wealthier people emit more CO_2 than poorer people. For example, the average per

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capita carbon footprint of people in the top 10% income level is almost three times higher than that of a typical person in an advanced country with a median income (Chancel, 2022). We argue that it is essential to understand the average per capita CO_2 emissions of more prosperous people (within the top 10% income threshold) because decreasing CO_2 emissions must begin with these people in society. This is because wealthy people have the financial sources to invest in less environmentally intensive production and consumption practices, unlike poor households.

At this juncture, this paper explores the factors driving CO_2 emissions inequality across countries. For this purpose, the article uses the panel dataset of 38 developed and developing countries from 1990 to 2019. The paper also focuses on the roles of gross domestic product (GDP) per capita, capital-labour ratio, globalisation and geopolitical risk on CO_2 emissions inequality. Previous empirical works have concentrated mainly on the determinants of CO_2 emissions. To put it differently, previous empirical papers have only considered the CO_2 emissions measure for developed and developing economies. The analysis for a mix of developed and developing countries shows that CO_2 emissions inequality is also a significant problem in these countries, which makes our study of CO_2 emissions inequality more relevant. Our paper provides a more comprehensive understanding of the factors contributing to CO_2 emissions inequality. We suggest that the findings of our paper provide a strong foundation for developing essential policy implications for reducing CO_2 emissions inequality.

According to the literature review of Heinonen et al. (2020), there are several previous studies examined the determinants of CO_2 emissions inequality. Still, they have been limited to regional or national data in large economies, such as China and the United States. For instance, Wang et al. (2022a), Wiedenhofer et al. (2017), and Xu et al. (2016, 2022) have investigated the cases in China, while Feng et al. (2021), Song et al. (2022), and Starr et al. (2023) have focused on the United States. These studies have obtained mixed findings on the determinants of CO_2 emissions inequality in those related countries.

Unlike previous papers, this paper argues several drivers of CO_2 emissions inequality across 38 developing and developed economies. First, CO_2 emissions inequality should be affected by a country's income level, typically measured by the GDP per capita. The Environmental Kuznets Curve (EKC) hypothesis proposed by Grossman and Krueger (1991, 1995) suggests a significant relationship between CO_2 emissions and GDP per capita. Initially, as an economy grows, CO_2 emissions increase. However, at a certain point, known as the threshold level, GDP per capita begins to reduce CO_2 emissions. This inverted U-shaped relationship between GDP per capita and CO_2 emissions has been supported by some studies (Dinda, 2004). Nevertheless, following the EKC hypothesis, we consider GDP per capita to analyse its impact on CO_2 emissions inequality. Since we include several developing economies, we expect a positive effect of GDP per capita on CO_2 emissions inequality.

We also suggest that globalisation is the second factor to drive CO_2 emissions inequality. Globalisation can help to reduce CO_2 emissions inequality by promoting the development and diffusion of new and more energy-efficient technologies (Gozgor et al., 2020; Liu et al., 2020; Rahman, 2020; Shahbaz et al., 2018; Yang et al., 2021; You and Lv, 2018). These technologies can help to reduce the amount of CO_2 emitted per unit of economic output, which can help to level the playing field between countries with different levels of economic development. Following previous findings, we also include the (overall) KOF globalisation index to control the role of globalisation in CO_2 emissions inequality in the panel data of 38 developing and developed economies. We expect a negative impact of globalisation on CO_2 emissions inequality.

The third variable for determining CO_2 emissions inequality is the capital-labour ratio. The capital-labour ratio is a measure of the amount of capital that is available for each worker in an open economy. A higher capital-labour ratio means more capital is available to each worker. We suggest that in countries with a higher capital-labour ratio, there is a greater tendency to use capital-intensive technologies (Krajewski and Mackiewicz, 2019; Lu et al., 2023). These technologies tend to be more in energy-intensive sectors (e.g., manufacturing and transportation), which should cause higher CO_2 emissions inequality. A high capital-labour ratio can also lead to more unequal income distribution since wealthy people often own capital (Saez and Zucman, 2020). Indeed, in countries with a high capital-labour ratio, the rich hold more capital than the poor people. This means the wealthy are responsible for a disproportionate share of CO_2 emissions. Following these arguments, we also consider the role of the capital-labour ratio and expect a positive impact of the capital-labour ratio on CO_2 emissions inequality.

The fourth is geopolitical risk, the primary variable of interest to drive CO2 emissions inequality. Previous findings have shown that geopolitical risk increases income inequality (e.g., Wu et al., 2022). Similarly, the higher geopolitical risk due to conflict and political instability can increase CO_2 emissions inequality. As we have observed from the Russia-Ukraine war since February 2022, geopolitical risk increases military spending. The geopolitical risk escalates CO_2 emissions inequality since military spending often involves using fossil fuels like oil and natural gas (Wang et al., 2022b). Geopolitical risk related to conflict or political instability can also disrupt energy infrastructure, including renewables, thus increasing CO_2 emissions inequality (Zhao et al., 2023; Shahbaz et al., 2023). In addition, geopolitical risk may hurt capital investments, and more energy-efficient production can be more costly with higher geopolitical risk (Gozgor et al., 2022). Geopolitical risk can also decrease imports and exports, leading to shortages or higher prices for goods and services. These issues can increase CO_2 emissions inequality. Therefore, we include the geopolitical risk index of Caldara and Iacoviello (2022) to control the impact of geopolitical risk on CO_2 emissions inequality in the panel dataset of 38 developing and developed economies.

To the best of our knowledge, this is the first empirical paper in the literature that examines the impact of geopolitical risk on CO_2 emissions inequality across developing and developed economies. For this purpose, we focus on the panel data set of 38 developed and developing economies from 1990 to 2019. In addition, we control for the effects of globalisation, capital-labour ratio, GDP per capita and geopolitical risk as the potential drivers of CO_2 emissions inequality. According to the empirical findings, geopolitical risk, capital-labour ratio, and GDP per capita increase CO_2 emissions inequality. However, globalisation decreases CO_2 emissions inequality. The pairwise panel heterogeneous causality test results align with these benchmark results and indicate no reverse causality issue. In a given economy under specific GDP per capita level and capital-labour ratio, we suggest that increasing globalisation and decreasing geopolitical risks are noteworthy to reduce CO_2 emissions inequality in leading developing and developed economies.

The rest of the paper is organised as follows. Section 2 explains the details of data sources and the model specifications. This section also provides the details of diagnostics tests and econometric methods. Section 3 discusses the empirical results, and Section 4 concludes.

2. Data, model specifications, and econometric methodology

2.1. Data sources and model specifications

The empirical analyses focus on 38 developed and developing countries[1] from 1990 to 2019. The paper uses CO_2 emissions inequality

[1] Argentina, Australia, Belgium, Brazil, Canada, Chile, China, Colombia, Denmark, Finland, France, Germany, Hong Kong SAR (China), India, Indonesia, Israel, Italy, Japan, Korea Republic, Malaysia, Mexico, the Netherlands, Norway, Peru, the Philippines, Portugal, Russia, Saudi Arabia, South Africa, Spain, Sweden, Switzerland, Thailand, Turkiye, Ukraine, the United Kingdom, the United States and Venezuela.

as the dependent variable. Specifically, we use the dependent variable of CO_2 emissions inequality (i.e., total carbon footprint per capita by the wealthiest 10% of the population). It is calculated using the estimations of Chancel (2022) based on input tables, national accounts, surveys, and tax data combinations.

Geopolitical risk is employed as the primary independent variable in the CO_2 emissions inequality function, and the related data are obtained from Caldara and Iacoviello (2022). Besides, we use the overall globalisation index, real GDP per capita, and capital-labour ratio as control variables. The overall globalisation index is obtained from Gygli et al. (2019). It captures the effects of economic integration, political integration, and technology on CO_2 emissions inequality. GDP per capita and capital-labour ratio are downloaded from Feenstra et al. (2015). GDP per capita captures the income effect, and the capital-labour ratio refers to productivity differences among the countries. A complete description of the above variables is presented in Table 1.

Based on the specification of the variables selected, we formulate the CO_2 emissions inequality function as follows:

$$CI_{it} = f(GPR_{it}, GI_{it}, KLR_{it}, GDPC_{it}) \tag{1}$$

Before analysing the model, we compress the variability of the data by taking a logarithmic transformation of all the variables except the GPR index. A logarithmic transformation would reduce extreme values' impact and linearise the non-linear relationship. This issue gives us a transformed model as follows:

$$logCI_{it} = \alpha_1 + \beta_1 GPR_{it} + \beta_2 logGI_{it} + \beta_3 logKLR_{it} + \beta_4 logGDPC_{it} + \varepsilon_{it} \tag{2}$$

Where *logCI, logGI, logKLR, and logGDPC* are the natural logarithm of CO_2 emissions inequality, overall globalisation index, capital-labour ratio, and real GDP per capita, respectively. *GPR* is the index of geopolitical risk. Furthermore, α_1 is the intercept of the model, and β_i ($i = 1,2,3,4$) are the coefficients of the independent variables. In addition, ε_{it} is the stochastic disturbance term of the model that captures the influence of omitted variables on the dependent variable. Finally, the subscript i is for the cross-sectional units (i.e., countries), while t indicates the study period (years). Following the previous paper, we expect the GDP per capita, GPR, and capital-labour ratio to increase CO_2 emissions inequality. However, globalisation should be negatively related to CO_2 emissions inequality. Therefore, we expect $\beta_1 > 0$, $\beta_2 < 0$, $\beta_3 > 0$ and, $\beta_4 > 0$.

2.2. Diagnostics tests and econometric methods

2.2.1. Cross-sectional dependence tests

Since panel data usually suffers from cross-sectional dependence, it is imperative to properly diagnose and address the cross-sectional dependence to ensure the results' validity and reliability. It occurs when the observations within the identical cross-sections (i.e., countries) are not independent. This issue is typically ascribed to the influence of some unobserved shared factors that impact all units, potentially in diverse manners. Keeping this in mind, we adopt the Breusch-Pagan Lagrange Multiplier (LM) (Breusch and Pagan, 1980) and Pesaran Scaled LM (Pesaran, 2021) tests to diagnose the cross-sectional dependence among the variables of the present study. The Breusch-Pagan LM test is robust to heteroscedasticity, which can be applied even when the error terms have different variances across the cross-sections (Baum, 2001).

In addition, the Breusch-Pagan LM test does not impose strict assumptions on the distribution of the error terms. It only requires that the errors are independent and identically distributed (i.i.d) and allows for arbitrary correlation structures. On the other hand, the Pesaran-Scaled LM test is consistent under weak cross-sectional dependence, which means it can detect even trim levels of spatial correlation. Similar to the Breusch-Pagan test, it can be applied even when the error terms vary across cross-sections or periods. Besides, it can be used for balanced and unbalanced panels (Pesaran, 2021).

2.2.2. Heterogeneity test of Blomquist and Westerlund (2013)

Panel heterogeneity refers to systematic differences or variations across individual entities or units in a panel dataset. It reflects the differences in the cross-sectional units' characteristics, behaviours, or relationships. Heterogeneity arises from unobserved individual-specific factors or elements that affect the dependent variable. Therefore, we use the heterogeneity test of Blomquist and Westerlund (2013) for the present analysis, which is robust to heteroscedasticity and autocorrelation. It does not assume homoscedasticity or the absence of serial correlation in the error terms, making it suitable for situations where these assumptions may be violated. Besides, it is consistent, meaning the test statistic converges to its actual value as the sample size increases. The Blomquist-Westerlund test provides more reliable inference in panel data analysis by accounting for cross-sectional dependence and individual-specific effects. This issue helps the statistical analysis capture the underlying relationships while controlling for panel heterogeneity (Blomquist and Westerlund, 2013).

2.2.3. Panel unit root tests

Panel unit root tests are employed to assess the stationarity properties of variables in a panel data set. More specifically, these determine if the variables of interest exhibit a unit root. Unit root signals the presence of non-stationarity, leading to a stochastic trend and convergence to a fixed mean over time. For the present analysis, we use the cross-sectional augmented IPS (CIPS) and Cross-sectional Augmented Dickey-Fuller (CADF) tests of Pesaran (2007) for checking the unit root. The CIPS test incorporates cross-sectional information by extending the IPS test statistic with additional terms that capture the cross-sectional dependency. It is considered superior to the Im, Pesaran, and Shin (IPS) test of Im et al. (2003), failing to account for cross-sectional dependence explicitly, leading to biased results. On the other hand, the CADF test, in addition to cross-sectional dependence, allows for individual-specific lag length selection and coefficient restrictions, accommodating the heterogeneity in unit root behaviour across units. These features make the CIPS and the CADF preferred for detecting unit roots in panel data.

2.2.4. Panel cointegration tests of Kao (1999) and Pedroni (1999, 2004)

Panel cointegration refers to the existence of long-run equilibrium relationships among variables in panel data. Cointegration implies that even though individual variables may be non-stationary, a stationary linear combination of these variables exists. This issue suggests that the variables have a stable long-term relationship unaffected by individual-specific characteristics. Therefore, we utilise the panel cointegration tests of Kao (1999) and Pedroni (1999, 2004) to understand this relationship. The Kao panel cointegration test is an extension of Engle and Granger's (1987) cointegration test for time series data, adapted explicitly for panel data. It accounts for both cross-sectional and time-series dependence in the data. Like the Kao test, the Pedroni test considers both cross-sectional dependence and the time-series properties

Table 1
Specification of variables and data sources.

Variable Type	Label	Specification of Variable	Data Source
Dependent Variable	CI	CO_2 Emissions Inequality: Total CO_2 Equivalent per Capita (CO_2 Emissions per Capita of the Wealthiest 10% of the Population)	Chancel (2022)
Independent Variable	GPR	Geopolitical Risk	Caldara and Iacoviello (2022)
Control Variables	GI	(Overall) Globalisation Index	Gygli et al. (2019)
	KLR	Capital-labour Ratio	Feenstra et al. (2015)
	GDPC	Real GDP per Capita (Purchasing Power Parity Based)	Feenstra et al. (2015)

of panel data. In addition, the Pedroni test allows for two types of cointegration: group-mean cointegration and individual-specific cointegration. The group-mean cointegration implies that the cointegrating relationship holds for all individuals in the panel. In contrast, individual-specific cointegration suggests that each individual has a unique cointegrating relationship. The null hypothesis of both tests is that no cointegration exists among the variables. In contrast, the alternative theory suggests at least one cointegrating relationship.

2.2.5. The PCSE, the FGLS, and the Driscoll-Kraay estimations

Considering the heterogeneity of slope coefficients and cross-sectional dependence, the present study adopted the Panel-correlated Standard Errors (PCSE) regression method introduced by Beck and Katz (1995). The primary advantage of the PCSE regression method is its ability to address the issue of correlated errors within panels. Furthermore, it mitigates the variable bias by effectively controlling for unobserved heterogeneity specific to individual panels. Additionally, the PCSE is ideal for panel data sets in which the cross-sections exceed the number of periods (Beck and Katz, 1995).

We also use the Feasible Generalized Least Squares (FGLS) method of Hansen (2007) and Driscoll-Kraay standard error (Driscoll and Kraay, 1998) regression methods for testing the robustness of the results obtained from the PCSE estimations. Like the PCSE, the FGLS is an extension of the Ordinary Least Squares (OLS) method that accounts for the specific characteristics of panel data, such as serial correlation and heteroscedasticity. Besides, it controls for the individual-specific effects through a fixed-effects or random-effects model. On the other hand, the Driscoll-Kraay standard errors estimate standard errors in regression models when there is potential correlation or heteroscedasticity in the error terms. Besides, it provides consistent and unbiased estimates of the standard errors, even when there is correlation or heteroscedasticity in the error terms (Hoechle, 2007).

Finally, to check the robustness of the findings, we utilise the pairwise panel heterogeneous causality test conducted by Dumitrescu and Hurlin (2012) to examine causality relationships between variables in a panel data set, considering heterogeneity among the individual units in the panel.

3. Empirical results and discussion

3.1. Descriptive statistics and pairwise correlations

Table 2 reports the descriptive statistics of the selected variables with 1140 observations. All the variables except the GI are positively skewed since their mean values are more significant than the median values. Furthermore, the mean values and the variance of the GDPC and the KLR are significantly higher than the mean values of other variables. All the variables, except the GPR, report higher deviations around the mean. Since this could give rise to significant variances, these variables have undergone a logarithmic transformation.

Table 3 outlines the pairwise correlation matrix of the variables of the present analysis. As evident, all the explanatory variables are significantly and positively correlated with the dependent variable. On the other hand, all the explanatory variables are positively and significantly correlated. Except for globalisation, the evidence aligns with the previous discussion from the earlier papers and the theoretical background in Eq. (1) and Eq. (2).

Table 2
Descriptive statistics.

Variable:	CI	GPR	GI	KLR	GDPC
Mean	34.44	0.220	70.47	243,707	27,272
Medium	30.75	0.065	71.01	237,450	26,972
Maximum	117.5	4.679	91.14	703,734	94,650
Minimum	3.269	0.004	32.01	7212	251.1
Standard Deviation	20.72	0.481	13.06	156,899	17,565
Skewness	1.113	5.143	−0.413	0.448	0.584
Kurtosis	4.389	33.58	2.414	2.354	2.963
Jarque-Bera	326.7	49,465	48.66	57.96	64.96
Observations	1140	1140	1140	1140	1140

Source: The authors' estimations.

Table 3
Pairwise correlations.

Variable	CI	GPR	GI	KLR	GDPC
CI	1.000				
GPR	0.377***	1.000			
GI	0.390***	0.102***	1.000		
KLR	0.583***	0.157***	0.760***	1.000	
GDPC	0.702***	0.212***	0.752***	0.869***	1.000

Note: ***$p < 0.01$.
Source: The authors' estimations.

3.2. Results of diagnostic tests

Table 4 presents the results for the cross-sectional dependence between the variables of interest obtained by the Breusch-Pagan LM test of Breusch and Pagan (1980) and the Pesaran-Scaled LM test of Pesaran (2021). Both tests reject the null hypothesis that no cross-sectional dependence exists among the variables. In other words, both results confirm the presence of cross-sectional dependence in the model. Since the results from Table 4 confirm the presence of cross-sectional dependence, it is essential to check for the heterogeneity and the unit-root properties of the variables of interest.

Table 5 reports the results of the heterogeneity test of Blomquist and Westerlund (2013). The results reject the null hypothesis of homogeneity and confirm the presence of heterogeneity in the model. This ensures the diversity of 38 developed and developing countries and reflects the complex and dynamic nature of the phenomena under investigation.

Table 6 presents the unit root results of the CIPS test of Im et al. (2003) and the CADF test of Pesaran (2007). The results reveal that the dependent variable possesses unit root (non-stationarity) at constant and trend levels. On the other hand, all the explanatory variables except the GDPC are stationary at the constant level under both tests. However, all the variables, except the KLR, are non-stationary at the trend level under the CADF test. Finally, all the variables are stationary at the first difference under both tests. This evidence means these variables exhibit first-order or I (1) integration.

The results presented in Table 7 indicate the long-term relationship of the explanatory variables with the CO_2 emissions inequality, according to Kao's (1999) panel cointegration test. On the other hand, seven out of eleven statistics are statistically significant under the Pedroni (1999, 2004) panel cointegration test. This issue makes us conclude that there exists a long-run relationship between the variables of the present model.

Overall, we observe that CO_2 emissions inequality maintains a long-term equilibrium relationship with the geopolitical risk in the presence of the control variables under consideration.

Table 4
Results of the cross-sectional dependence tests.

Variable	Breusch–Pagan LM	Pesaran–Scaled LM
logCI	5408***	125.4***
GPR	2278***	42.02***
logGI	18,545***	475.8***
logKLR	14,425***	365.9***
logGDPC	15,419***	392.4***

Note: ***$p < 0.01$.
Source: The authors' estimations.

Table 5
Results of the heterogeneity test of Blomquist and Westerlund (2013).

Adj.	Delta
	22.47***
	25.13***

Note: ***$p < 0.01$.
Source: The authors' estimations.

Table 6
Results of the CIPS and the CADF panel unit root tests.

Variable	Constant		Constant and Trend	
	Levels	Δ	Level	Δ
Panel A: Results of the CIPS Panel Unit Root Test				
LogCI	−2.053	−5.302***	−2.466	−5.488***
GPR	−3.097***	−5.744***	−3.41***	−5.858***
logGI	−2.888***	−5.396***	−2.897***	−5.442***
logKLR	−2.716***	−3.310***	−2.879***	−3.751***
logGDPC	−1.556	−3.630***	−2.071	−3.961***
Panel B: Results of the CADF Panel Unit Root Test				
logCI	−1.495	−2.648***	−1.829	−2.918***
GPR	−1.955***	−3.423***	−2.245	−3.495***
logGI	−2.153***	−3.233***	−2.267	−3.303***
logKLR	−2.592***	−2.673***	−2.923***	−2.782***
logGDPC	−1.934	−2.364***	−2.230	−2.620**

Note: ***$p < 0.01$ and **$p < 0.05$, Δ = First difference.
Source: The authors' estimations.

Table 7
Results of the panel cointegration tests.

Panel A: Residual Cointegration Test of Kao (1999)

t-statistic Prob. ADF = 3.282*** 0.0005

Residual Variance = 0.0019 HAC Variance = 0.0010

Panel B: Residual Cointegration Test of Pedroni (1999, 2004)
Null Hypothesis: No Cointegration
Alternative Hypothesis: Common AR Coefficients (within–dimension)

	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-statistic	0.559	0.287	0.062	0.475
Panel rho-statistic	−5.870***	0.000	−0.586	0.278
Panel PP-statistic	−21.26***	0.000	−6.572***	0.000
Panel ADF-statistic	−6.674***	0.000	−2.245**	0.012

Alternative Hypothesis: Individual AR Coefficients (between–dimension)

	Statistic	Prob.
Group rho-statistic	1.461	0.928
Group PP-statistic	−7.365***	0.000
Group ADF-statistic	−1.648**	0.049

Note: ***$p < 0.01$ and **$p < 0.05$.
Source: The authors' estimations.

3.3. Results of regressions estimations and discussion

3.3.1. Geopolitical risk and CO_2 emissions inequality

Table 8 outlines the long-term coefficients of the model using the PCSE, the FGLS, and the Driscoll-Kraay regression techniques. These results confirm a significant positive impact of geopolitical risk on CO_2 emissions inequality. More specifically, the findings validate that the increasing geopolitical risk exacerbates the CO_2 emissions inequality in 38 developing and developed countries. Geopolitical risks can affect the availability and price of resources, including carbon and fossil fuels (Lau et al., 2023). In times of uncertainty and instability, the wealthy population may respond by increasing their resource consumption to secure their positions or protect their assets. This issue can result in higher energy consumption, including using carbon-intensive sources, such as fossil-fuel-backed vehicles or large estates.

In contrast, lower-income individuals may lack the means to increase their consumption levels or access more sustainable alternatives, thus widening the CO_2 emissions gap. In the worst-case scenario, lower-income individuals may experience financial constraints and prioritise basic necessities, limiting their ability to invest in sustainable products or adopt low-carbon lifestyles. Furthermore, wealthier individuals often have more influence on policy decisions and regulations. As a result, they may lobby for policies that prioritise their interests and allow for more lenient environmental standards or exemptions, leading to higher CO_2 emissions. This issue can result in unequal regulatory frameworks that benefit wealthy individuals and perpetuate CO_2 emissions inequality. This issue allows them to continue high-emissions activities while disproportionately burdening lower-income individuals.

Additionally, geopolitical instability may create opportunities for resource exploitation in regions with weaker environmental regulations, further encouraging investments that perpetuate carbon-intensive practices and widening the already existing CO_2 emissions inequality in the related countries.

Finally, increased geopolitical risk weakens the existing environmental rules and delays the adoption of new approaches. This issue could further perpetuate CO_2 emissions inequality if it allows the wealthy to continue emitting carbon while transferring the responsibility for CO_2 emissions reduction onto lower-income individuals or communities.

3.3.2. The roles of control variables in driving CO_2 emissions inequality

Table 8 further reveals that globalisation negatively and significantly affects CO_2 emissions inequality. This evidence means that opening 38 developed and developing economies leads to processes that promote sustainable environmental practices from the wealthiest, reducing their CO_2 emissions and the existing CO_2 emissions inequalities. This issue is possible since technology can promote sustainable consumption patterns by providing access to eco-friendly products, raising awareness about the environmental impact of consumption, and supporting responsible business practices. As sustainability becomes more valued globally, the wealthiest individuals within countries may adopt greener lifestyles, reducing CO_2 emissions. In addition, globalisation creates a global marketplace where consumer preferences and market forces

Table 8
Results of regression estimations.

Method	PCSE		FGLS		Driscoll-Kraay	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
GPR	0.028***	0.009	0.035***	0.000	0.079***	0.010
logGI	−0.194*	0.116	−0.651***	0.004	−1.069***	0.117
logKLR	0.169***	0.043	0.046***	0.001	0.289***	0.078
logGDPC	0.371***	0.041	0.757***	0.001	0.549***	0.129
Constant Term	−0.693***	0.159	−0.866***	0.005	−0.490**	0.235

Note: ***$p < 0.01$, **$p < 0.05$ and * $p < 0.10$.
Source: The authors' estimations.

influence business practices. As sustainability becomes increasingly valued, there is a growing demand for eco-friendly products and services. The wealthiest population can drive market demand for sustainable goods and services with greater purchasing power. In response, businesses may adopt greener practices, develop sustainable products, and invest in cleaner technologies to cater to this demand. This shift towards sustainable consumption can result in reduced CO_2 emissions from the products consumed by the wealthiest individuals. Lastly, more affluent individuals often consume products that have complex and global supply chains. Promoting sustainable practices throughout the supply chain, such as responsible sourcing, energy-efficient manufacturing, and low-emissions transportation, reduces the carbon footprint of producing and distributing goods consumed by the wealthiest population. A reduction in CO_2 emissions reflects immediately on the CO_2 emissions inequality within 38 developed and developing countries.

In addition, it is evident from Table 8 that the capital-labour ratio positively and significantly influences CO_2 emissions inequality. Increasing capital intensity relative to labour worsens pre-existing imbalances in the CO_2 emissions between the wealthiest and the poorest. As the capital-labour ratio increases, industries adopt more capital-intensive technologies to enhance productivity and profitability. These technologies often rely on fossil fuels or energy-intensive processes, which can lead to higher CO_2 emissions inequality. Furthermore, the rising capital-labour ratio often leads to the growth of high-income sectors such as manufacturing, construction, and transportation. These sectors typically have a higher carbon footprint due to their reliance on energy-intensive processes, fossil fuel consumption, and CO_2 emissions from transportation activities. In addition, the wealthiest individuals within a country often have a higher representation and involvement in these sectors, either as business owners, investors, or high-income employees, thus contributing to their higher CO_2 emissions inequality. Finally, the wealthiest individuals tend to have higher carbon-intensive lifestyles, with larger residences, multiple vehicles, air travel, and luxury goods. The rising capital-labour ratio can fuel economic growth, increase income inequality, and exacerbate the carbon-intensive lifestyles of the rich, leading to higher CO_2 emissions inequality.

Finally, Table 8 reveals that economic growth positively and significantly affects CO_2 emissions inequality within 38 developed and developing countries. It indicates that these countries are yet to reach the stage of economic growth that would initiate a decline in the overall CO_2 emissions quantity and the resultant CO_2 emissions inequality, as projected by the EKC hypothesis. In pursuit of economic growth, the focus often lies on maximising profits and expanding production, sometimes at the expense of ecological considerations. This issue can lead to the neglecance of sustainable practices and a reliance on carbon-intensive technologies. Moreover, the wealthiest population, with more significant influence and decision-making power, may prioritise economic gains over environmental concerns, leading to higher CO_2 emissions inequality. Besides, economic growth fosters increased consumption, benefits carbon-intensive sectors, promotes energy-intensive lifestyles, neglects sustainability considerations, and sometimes even creates unequal access to clean technologies. All these factors potentially perpetuate the unequal CO_2 emissions scenario.

3.4. Robustness check: panel causality tests

Finally, we examine the direction and strength of causality between the selected variables using the Pairwise Panel Heterogeneous Causality test developed by Dumitrescu and Hurlin (2012). These results are presented in Table 9.

As expected, a significant causality runs from geopolitical risk to CO_2 emissions inequality. Similarly, unidirectional causality flows from per capita income to CO_2 emissions inequality and from globalisation to CO_2 emissions inequality are also observed. In addition, a bidirectional causality exists between the capital-labour ratio and CO_2 emissions inequality. These findings further validate our model and confirm a significant influence of the selected variables on the outcome variable, meaning that there is no reverse causality issue between the GPR and CO_2 emissions inequality.

Table 9
Pairwise panel heterogeneous causality test of Dumitrescu and Hurlin (2012).

Null Hypothesis	W-Stat.	Zbar-Stat.
GPR does not homogeneously cause logCI	2.999	2.059**
logCI does not homogeneously cause GPR	4.732	6.501
logGI does not homogeneously cause logCI	1.655	−1.367*
logCI does not homogeneously cause logGI	2.291	0.258
logKLR does not homogeneously cause logCI	6.164	10.16***
logCI does not homogeneously cause logKLR	3.299	2.835***
logGDPC does not homogeneously cause logCI	6.423	10.82***
logCI does not homogeneously cause logGDPC	2.454	0.676

Note: ***$p < 0.01$, **$p < 0.05$ and * $p < 0.10$.
Source: The authors' estimations.

4. Conclusion

This paper investigated the impact of geopolitical risk on CO_2 emissions inequality in the panel dataset of 38 developed and developing economies from 1990 to 2019. We controlled for the effects of globalisation, capital-labour ratio, and per capita income on CO_2 emissions inequality. After checking various diagnostics, the panel cointegration test of Kao (1999) and Pedroni (1999, 2004) indicated a significant long-run relationship among the related variables. The PCSE, the FGLS, and the Driscoll-Kraay estimations showed that geopolitical risk, capital-labour ratio, and per capita income increase CO_2 emissions inequality. In contrast, globalisation is negatively associated with CO_2 emissions inequality in the panel dataset of 38 developed and developing countries. The pairwise panel heterogeneous causality test indicated no reverse causality issue for the relationship between the GPR and CO_2 emissions inequality.

The findings suggest that addressing the CO_2 emissions inequality resulting from rising geopolitical risk requires a combination of policy interventions, including progressive taxation, equitable regulation, and targeted support for low-income communities. In addition, encouraging sustainable consumption and production patterns, promoting renewable energy access, and strengthening environmental regulations can help reduce the CO_2 emissions gap between rich and poor people. This paper highlights the importance of addressing the environmental implications of consumption patterns and promoting sustainable practices among affluent individuals to reduce CO_2 emissions and foster higher equity in carbon footprints in the related countries.

It is important to note that our findings are limited to the panel dataset of 38 developing and developed economies. Future papers on this subject can focus on other potential determinants of CO_2 emissions inequality across more developing and developed countries. For instance, an important research question is how different institutions affect CO_2 emissions inequality. Time-series analyses on the single country case (e.g., China and India) can also provide interesting findings.

CRediT authorship contribution statement

Limei Chen: Writing – original draft. **Giray Gozgor:** Supervision, Writing – original draft. **Chi Keung Marco Lau:** Methodology, Software. **Mantu Kumar Mahalik:** Software, Validation. **Kashif Nesar Rather:** Conceptualization, Investigation. **Alaa M. Soliman:** Writing – review & editing.

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.

Data availability

Data will be made available on request.

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