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Research article

Modeling green energy and innovation for ecological risk management using second generation dynamic quantile panel data model

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A R T I C L E I N F O

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A B S T R A C T

Ecological risk management has emerged as a critical research and policy development area in energy and environmental economics. Sustained ecology is crucial for the standard of living and food security. As the adverse impacts of environmental degradation and climate change become increasingly apparent it is imperative to understand ecological risk and its interconnectedness with environmental pressure, clean energy, economic activity, globalization, and green technology. Ecological risk is assessed using the environmental performance index which is a holistic indicator of climate change, environmental pressures and human actions in which most of these indicators have spatial effects. This paper explores the multifaceted relationship between identified anthropogenic critical factors and their role in effectively managing ecological risk globally. This study has developed the second-generation dynamic panel quantile regression considering spatial effects of economic activities on ecology across borders of 55 countries between 1995 and 2022. This innovative hybrid estimation scheme that integrated theoretical and econometric aspects makes the model robust to major regression issues. Several implications ranked in decreasing order of its effectiveness are reducing environmental pressure, expediting energy transition, and embracing economic integration while there is a need to work on rejuvenating green technology and green growth.

Acronyms

Symbol	Name
ADF	Augmented Dickey Fuller Test
ARDL	Auto-Regressive Distributed Lag
ASEAN	Association of Southeast Asian Nations
CCEMG	Common Correlated Effects Mean Group
CD	Cross-sectional dependence
CIPS	Cross-sectional Im Pesaran Shin Test
CO2	Carbon Dioxide
COP27	Conference of the Parties 27
DFE	Dynamic Fixed Effect
ECM	Error Correction Model
EKC	Environmental Kuznets Curve
EPA	Environmental Protection Agency
EPI	Environmental Performance Index
GDP	Gross Domestic Product
IPCC	Intergovernmental Panel on Climate Change
ISO14001	International Standard Organization
KOF	Konjunkturforschungsstelle Swiss Economic Institute
LM	Lagrange Multiplier
LULC	Land Use and Land Cover
M&TNC	Multinational and Transnational Corporations
OECD	Organization for Economic Co-operation and Development
PP	Phillip Perron
WDI	World Development Indicators

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1. Introduction

The 21st century presents a unique set of challenges for societies across the globe as environmental degradation and climate change pose unprecedented risks to ecosystems and human well-being. The Intergovernmental Panel on Climate Change (IPCC) (2018) indicates that persistent environmental degradation may permanently damage the ecosystem. This biodiversity contributes to half of the world's GDP (World Bank, 2021). Many industries benefit from the diverse biota (Hoffmann, 2022) as input and the environment building up the climate change resilience. Considering these challenges, studies are required to assess the socio-economic and technological factors' role with ecological risk. National ecological risk mitigation risk efforts are required because of diverse environmental conditions and socio-economic dynamics across countries (Zhang et al., 2022). Literature has coined ecological risk as a potential harm to ecosystems and their associated services caused by natural or human factors. These risks are a threat to the stability of the ecosystem which includes pollution, species extinction, habitat destruction, natural disasters, and climate change. Managing these challenges in diverse geographical and ecological contexts demand studies that can form strategies for mitigation and adaptation (Landis et al., 2013) which can understand the nature and magnitude of the ecological risk at national level and provide targeted interventions.

The anthropogenic activities that led to the loss of ecosystem services, had increased healthcare costs and other pollution related diseases (Fatima et al., 2021), has disrupted agricultural productivity (Arshed and Abdulqayumov, 2016), and caused damage to infrastructure. Healthy ecosystem services help economic activities and improve public health and well-being using facilities like clean air and water, fertile soils, climate regulation and diverse biota. Failing to stabilize these services could undermine national resilience to climate change thus necessitating an integrated approach to explore environmental, economic and social dimensions of ecological risk. The outcomes of this effort can lead to interdisciplinary collaborations, stakeholder engagement, and scientific knowledge integration. This study contributes to this domain by exploring role of environmental pressure, clean energy, economic activity, globalization and green technology on ecological risk using robust econometric assessment at national level.

Ambient air pollution has the highest share in ecological risk as it represents the ecosystem's integrity and health. This risk can originate from mold, suspended particles, scarcity of green fields, or an inability to trap carbon (Sampson, 2012). The current air pollution must be trapped within Earth in order to improve ecological quality (Berger et al., 2017) and for the US Environmental Protection Agency to assess and improve ecological risk (EPA, 1998).

The transition to clean energy sources, such as renewables and low-carbon technologies, is vital in mitigating ecological risk. Renewable energy reduces greenhouse gas emissions and curbs air and water pollution associated with conventional energy sources. It also increases business competitiveness (Rusinko, 2007). The recent COP27 has highlighted the complete transition towards renewable energy. The behavior of clean energy consumption helps control the environmental impacts which take the pollution from energy consumption processes (Wang and He, 2006). Improving clean production levels and the proportion of new energy resources could effectively save and mitigate air pollutants and CO_2 emissions (Chen et al., 2018) where biomass energy consumption has shown great potential (Danish and Wang, 2019). Numerous studies have highlighted the negative correlation between renewable energy deployment and CO_2 emissions (IPCC, 2018; Yu-Ke et al., 2022; Zahid et al., 2020). As countries increase their reliance on renewable energy, they are able to curb greenhouse gas emissions simultaneously. However, there is a need to explore if it can decrease their ecological risk (Arshed et al., 2024).

While driving growth and prosperity, economic activities can also pose significant ecological risks. Environmental economists advocate for delinking economic progress with environmental deterioration. Industrial production, agriculture, transportation, and urbanization pressure natural resources and ecosystems. Balancing economic development with ecological sustainability is a complex task that requires effective policy instruments and innovative strategies. Species endangerment is highly correlated with population and GDP, and per capita GDP is a significant regressor of species endangerment (Czech et al., 2012). The findings of Kirikkaleli et al. (2020) reveal that (i) in the long run globalization impacts ecological footprint positively and (ii) trade openness reduces ecological footprint in the short run while ecological footprints are negatively affected by GDP growth in both the short and the long run. Stern et al. (1996) highlighted the need to decouple the link between economic activity and environmental degradation to achieve environmental sustainability and another study iterated decoupling against biodiversity (Arshed et al., 2024).

Ecological risks are also connected with the interconnection between different ecologies globally. The changes in human living practices, infrastructural changes, introduction of new foods and non-native animals in the ecology do have unpredictable effects (Landis et al., 2013). Globalization has transformed the global economic landscape, enabling the flow of goods, services, and capital across national boundaries. While globalization brings economic benefits it also intensifies ecological risks through increased resource consumption, pollution emissions, and ecological degradation. The findings of Teng et al. (2020) show that globalization adversely and significantly influences environmental degradation; globalization reduces environmental degradation in the long run while globalization positively and significantly influences environmental degradation in the short run. Political globalization is shown to be a tool for mitigating environmental degradation while economic globalization harms it (Leal and Marques, 2020; Zandi and Haseeb, 2019). On the one hand, globalization enables the dissemination of green technologies and expertise, facilitating the adoption of sustainable practices worldwide (Kolk et al., 2008). Similarly, globalization led increased trade and consumption (scale effect) of natural resources can cause degrade environment and escalate ecological risk (Sachs and Warner, 2001). It calls for exploration and careful management in order to reduce ecological risks.

Long term growth is reliant on technological innovation (Romer, 1986) but sustainability arrives when this technology reduces the dependency on natural resources (Han et al., 2022; Zhang et al., 2023) rather than using scale effect to increase natural resource demand (Mirza et al., 2019). In this premise, green technologies play a vital role in promoting sustainable development. These technological advancements include energy efficiency, waste reduction, economic circularity, and resource management which can initiate low-carbon transition and minimization of footprints. Vienneau et al. (2017) showed that green technology can reduce mortality risk and increase environmental exposure resilience. Its development contributes in environmental sustainability (Ismail et al., 2013) and climate change resilience (Arshed et al., 2023). Nizam et al. (2020) conclude that green technology is imperative for achieving long-term sustainable growth in a country along with green energy (Doğan et al., 2020a). Studies have shown that green technology can significantly mitigate ecological risk (Acemoglu et al., 2016).

By unraveling the interplay between ecological risk and clean energy, environmental pressure, economic activity, globalization, and green technology, this study aims to comprehensively understand the determinants of ecological risk at national level. The following are the proposed research questions.

a. What is the long run role of renewable energy on ecological risk after accounting for major estimation issues of panel data?
b. What is the long run role of environmental pressure on ecological risk after accounting for major estimation issues of panel data?
c. What is the long run role of globalization on ecological risk after accounting for major estimation issues of panel data?

d. What is the long run role of economic activity on ecological risk after accounting for major estimation issues of panel data?
e. What is the long run role of green technology on ecological risk after accounting for major estimation issues of panel data?

Through an analysis of theoretical frameworks and empirical evidence, this study seeks to contribute to the body of knowledge on sustainability and provide valuable insights for policymakers, researchers, and stakeholders striving to address the pressing challenges of environmental degradation and achieve a more sustainable future. This study also highlights the gains from globalization and clean energy as potential indicators of reducing ecological risk across all quantiles while there is a need to explore the reasons behind the ineffectiveness of green technology.

Following the introduction in the first section, this study explores the theoretical and empirical link between the selected variables and ecological risk in Section 2. Section 3 discusses data and methods, followed by results and discussions in Section 4.

2. Theoretical and empirical review

The carbon emissions and risk relationship is complex as it involves feedback mechanisms building up climate change over time. By 2009 there was 70 million tons of CO_2 emissions per day (Kannan and James, 2009) creating a major ecosystem stressor (Lu et al., 2018). Lu et al. (2018) showed that a consistent increase in CO_2 via feedback loops would heat up the environment thereby causing melting of polar ice. This feedback effect amplifies the negative effect on ecosystem. Theoretical frameworks, such as tipping points and threshold effects, explain how increasing CO_2 emissions can push ecosystems beyond their resilience limits, resulting in abrupt and irreversible ecological changes (Cho, 2021). Anthropogenic activities led to CO_2 emissions significantly affecting the biodiversity scenario 2100 (Sala et al., 2000). CO_2 increases lead to changes in many marine life characteristics, devastatingly affecting marine ecology (Doney et al., 2012), and may lead to the risk of extinction by 2100 (Gattuso et al., 2015). High carbon-intensive businesses may deprive older people, pregnant women, and children of better lives (Belokon' et al., 2019).

In the case of Chinese iron and steel companies interview with a sample of 85 questionnaires, CO_2 reduction practices play a significant role in environmental performance. (Zhang et al., 2012). Regulations on CO_2 enhance environmental performance in the case of US coal power plants (Sueyoshi and Goto, 2010). Proper planning in forestation is required to ensure that carbon absorption leads to biodiversity recovery (Di Sacco et al., 2021).

The environmental Kuznets curve (EKC) has confirmed the link between economic activity and ecological risk (Stern et al., 1996). Literature has discussed the GDP effect on ecological indicators like species extinction, water pollution, and deforestation concluding its role in ecological risk. The GDP – ecological risk relationship can be studied under scale and composition effects. Scale effect explains the proportional relationship between growth and resource consumption leading to emissions and ecological risk (Li et al., 2014). Hereby growth leads to higher demand for energy, natural resources, and mechanization for increased extraction, production, and waste generation. While composition effect relates to the economy's structural transformation from agriculture/primary goods to industry/value-added goods, service sector transition can reduce ecological risks due to resource intensity decrease. Studies by Ang (2007) and Shafik and Bandyopadhyay (1992) had provided details on the scale and composition effect of GDP.

Türkiye experienced a positive GDP to footprint link (Udemba, 2020) but GDP positively effects environmental performance in a 78 country analysis (Kumar et al., 2019) and for 31 provinces of China between 1989 and 2009 (Li et al., 2014). Yang et al. (2012) concluded no effect of GDP on environment in the Zhejiang province of China. Similar results are confirmed using a super learner algorithm on global data (Kartal et al., 2024a).

Economic globalization, marked by trade and investment liberalization, can contribute to ecological risk through several channels. The expansion of international trade leads to increased production, resource extraction, and transportation, resulting in higher pollution levels and ecological degradation (Dasgupta and Chattopadhyay, 2004). Globalization often involves the international division of labor where production processes are fragmented across different countries. This division of labor can lead to environmental outsourcing, where countries with weak environmental regulations attract polluting industries (Akbostanci et al., 2007), shifting the ecological risk to these regions which is termed as Halo effect (Doytch and Uctum, 2016). Arshed et al. (2024) explored 66 country sample to conclude positive globalization effect on natural habitats which is an indicator of ecological risk.

Hornborg (1998) proposed ecologically unequal exchange framework proposing that globalization leads to ecological risk by ecological burden transferring to low developed countries (LDCs). Multinational corporations (MNCs) contribute in shaping the globalization and ecological risk relationship. MNCs pursuing for profits and market share operating in agriculture, manufacturing and extractive sectors can create environmental implications in terms of unsustainable resource extraction, pollution and deforestation causing ecological risks (Barbier, 2007; Buckley et al., 2019).

Corresponding to them, a study by Ebrahimi et al. (2021) assessed Italy and Japan for their collaboration as globalization indicators on air, water, and waste pollution; the results showed that globalization had led to improvement in ecological factors in both countries. Similar results were concluded from a 148-country study by Wang et al. (2021). The reason behind this is that globalization leads to firm-level self-regulation as confirmed in the case of China (Christmann and Taylor, 2001; Zhu and Sarkis, 2004).

Developing clean energy infrastructure, such as wind and solar farms, often requires land use, potentially impacting local biodiversity. However, clean energy installations generally have lower biodiversity impacts than fossil fuel extraction or large-scale hydropower projects. Furthermore, the mitigation of climate change through clean energy adoption helps safeguard the environment (Doğan et al., 2020b, 2022; Kartal, 2022, 2023) and ecosystems, and protect biodiversity from the adverse effects of global warming (Strassburg et al., 2018; Tittensor et al., 2014), energy security (Kartal et al., 2024b), and natural resource utilization (Li et al., 2024). Studies have shown that a 1% increase in renewable energy would lead to an improvement in the environment by 0.59% in E7 (Gyamfi et al., 2021) and 0.17% in ASEAN (Anwar et al., 2021). Multiple scenarios for Chinese provinces also showed that green energy does improve the Environmental Performance Index (Abbas et al., 2021).

Urbanization as an indicator of increased economic activity involves the conversion of natural habitats into built-up areas resulting in land use change and habitat fragmentation which disrupts biodiversity (Alberti et al., 2003; Foley et al., 2005) and human well-being. With increased economic activity in urban city centers, there is increased demand for water purification, climate regulation and biodiversity conservation and failing to provide these ecosystem services leads to ecological risk (Costanza et al., 2014; Millennium Ecosystem Assessment, 2005). The concentration in urban centers creates a heat island effect because of the replacement of natural vegetation with concrete surfaces. The urban heat island effect can lead to various ecological impacts including changes in microclimates, altered species distributions, and increased energy demand for cooling, further exacerbating ecological risks (Oke, 1982; Sailor, 2011). In China, urbanization rose from 17.9% to 54.8% between 1978 and 2014 which led to an increase in it's ecological footprint and a depreciation in environmental performance while some aspects of environmental performance improved in terms of an increase in waste treatment infrastructure (Huang et al., 2016). A study in Iran showed that there was a fall in vegetation coverage from 37.3% to 14.54% between 1987 and 2018 because of an increase in roads and the build up of areas has led to an increase in the natural climate change risk by 3.62%, the most prominent of which is the increase in soil erosion (Esmaeilzadeh and Ehteshami, 2020). Excessive land use/land cover (LULC) changes represent a satellite imagery method to assess urbanization and have an impact on several dimensions of Sustainable Development Goals in Türkiye (Agdas and Yenen, 2023).

Green innovation helps in improving resource efficiency and conservation. It reduces the ecological risk from resource extraction and depletion. Patents promote sustainable practices like circularity, energy efficiency, and recycling that reduce the demand for natural resources and waste generation. This green innovation is expected to mitigate ecological risks (Geissdoerfer et al., 2017; Mignacca et al., 2020). Green technology can help the transition towards cleaner energy, energy efficient mechanism, and waste management which helps reduce air and water pollution.

Theoretical frameworks, such as life cycle assessment and environmental impact analysis, highlight the link between green technology adoption and reduced ecological risk through pollutant emission reduction (Bovea and Powell, 2016). Studies have also shown that adopting green technologies reduces environmental footprints (Lenzen et al., 2018; Wiedmann et al., 2015).

A subregional analysis in Italy showed that an increase in green technologies positively affected environmental productivity in 2005 (Ghisetti and Quatraro, 2017). Green technology generated from internal factors (pollution reduction and green supply chain) and external factors (sustainable product development) implemented by ISO14001 adoption does diminish environmental impacts in 3490 firms from 58 countries (Miroshnychenko et al., 2017).

2.1. Literature gap

Literature has pointed out essential ecological risk indicators including GDP, globalization, clean energy, urbanization, environmental pressure, and green technology but this specific combination, along with the theoretical and statistical treatment of estimation issues, had been scarcely discussed. While assessing research between the years 1995 and 2022, most studies overlooked issues like heteroskedasticity, non-stationarity, cross-sectional dependence, and non-normality of the data among other estimation issues of panel data analysis. This study assesses 55 countries using the Panel Quantile Regression with Dynamic Fixed Effect (Arshed et al., 2022) and Common Correlated Effects Mean Group (Pesaran and Tosetti, 2011) as a novel estimation strategy to make the model robust to the said issues which makes the estimates robust, efficient, and suitable for inference. Empirical study like Ul-Durar et al. (2024) have used this estimation method integration approach.

3. Methods

3.1. Data and variables

This methods section starts with variable descriptions, estimation equations, and the estimation econometric method.

Table 1 details all the variables selected for this study, including their units and sources. Here the Environmental Performance Index (EPI) is used as a dependent variable while other variables are used as independent variables. The data is collected for 55 countries (Table 7 in the appendix).

3.2. Methodology and econometric methods

This study focuses on ecological risk which is a global issue (Heading and Cavaciuti-Wishart, 2024) where not all countries are equally affected (Bhargava and Bhargava, 2023). Most of the risks faced today are accumulated from past human activities and these challenges are not

Table 1
Variables and their data sources.

Name (Symbol)	Definition and Units	Source
Ecological Risk/Ecological Sustainability (EPI)	A scorecard to assess environmental performance (0–100)	Wolf et al. (2022)
Gross Domestic Product (LGDP)	Real GDP per capita US$ (Natural Log)	WDI (2021)
Globalization (KOF)	Index (0–100)	KOF Swiss Economic Institute (Gygli et al., 2019)
Clean Energy (RENE)	Renewable energy consumption as % of total energy consumption	WDI (2021)
Environmental Pressure/ Environmental Pollution (CO_2)	CO_2 emissions per capita	British Petroleum (bp, 2022)
Green Technology (TECH)	Green technology investment % of GDP	OECD (2023)

concentrated within country factors but rather it has across border effects. These four dimensions discussed led to the selection of a panel data sample for global generalization of effects using quantile-based estimates robust to outliers. The dynamic specification is used to allow for the past (lagged) effects and second-generation model is used to allow for cross country spill-over effects (cross sectional dependence). These theoretical and applied aspects motivated this study to explore global data and form a second-generation panel quantile ARDL model.

Using the variables from Table 1, the following Equation (1) is the primary statistical equation this study estimates. Here, the subscript 'i' describes countries, and 't' describes the time periods leading to an unbalanced panel data with white noise error 'e'.

$$EPI_{it} = \alpha_1 + \alpha_2 LGDP_{it} + \alpha_3 KOF_{it} + \alpha_4 RENE_{it} + \alpha_5 CO2_{it} + \alpha_6 TECH_{it} + e_{it} \tag{1}$$

Since the number of years per country is more than 19 this study cannot assume the data to be stationary (Eberhardt, 2012), thus there are statistical and theoretical reasons to use dynamic models. Further, with many cross-sections this study considers the presence of cross-sectional dependence in estimating the effects of selected management practice interventions for ecological risk management. These characteristics are tested using second-generation panel unit root and cross-sectional dependence tests.

This study integrates the Common Correlated Effects Mean Group (CCEMG) model (Kapetanios et al., 2011; Pesaran, 2006; Pesaran and Tosetti, 2011) to address cross sectional dependence. Studies like Iqbal et al. (2024) have used CCEMG model to determine biodiversity as an important component of ecological risk. This CCEMG model is used for non-stationary cross-sectional dependent variables with the Two Step Error Correction Model (ECM) model to form the Quantile Autoregressive Distributed Lag (ARDL) model for estimating distribution robust long run and short run estimates (Arshed et al., 2022, 2024; Iqbal et al., 2023; Ul-Durar et al., 2023) to propose second generation Panel Quantile ARDL. Here the Panel Quantile ARDL setup enables researchers to estimate marginal impacts at tails or any specified quantile position (Wang et al., 2024). The long-run estimates would be estimated using Equation (2) whereby the cross-sectional average forms (from α_8 to α_{13}) are used (Chudik and Pesaran, 2015) to absorb the cross-sectional dependence effect according to the CCEMG model (Adeneye et al., 2021).

$$\begin{aligned} EPI_{it} = {} & \alpha_{1i} + \alpha_2 LGDP_{it} + \alpha_3 KOF_{it} + \alpha_4 RENE_{it} + \alpha_5 CO2_{it} + \alpha_6 TECH_{it} \\ & + \alpha_7 \overline{LGDP}_i + \alpha_8 \overline{KOF}_i + \alpha_9 \overline{RENE}_i + \alpha_{10} \overline{CO2}_i + \alpha_{11} \overline{TECH}_i + e_{it} \end{aligned} \tag{2}$$

The short-run estimates are generated using the ECM specification in Equation (3). Here, the variables with Δ show short-run effects, the variables with lag are long-run multipliers, δ_2 denotes the convergence coefficients, and the variables with coefficients from β_8 to β_{13} are long-run cross-sectional dependence absorbers. Since they are time-invariant, their lags are the same as present and their first difference forms will be dropped. The intercept in both equations varies across cross sections making this model a Dynamic Fixed Effect (DFE) type of ARDL model (Blackburne and Frank, 2007). This study has estimated this second-generation Quantile ARDL model with DFE specification for the 25th, 50th, and 75th percentiles in order to explore the changes in the coefficients across the distribution. For incorporation of policy sensitivity, the algorithm can include more distribution positions.

$$\begin{aligned}\Delta EPI_{it} = {} & \beta_{1i} + \alpha_2 \Delta LGDP_{it} + \alpha_3 \Delta KOF_{it} + \alpha_4 \Delta RENE_{it} + \alpha_5 \Delta CO2_{it} \\ & + \alpha_6 \Delta TECH_{it} + \delta_2 EPI_{it-1} + \beta_2 LGDP_{it-1} + \beta_3 KOF_{it-1} + \beta_4 RENE_{it-1} \\ & + \beta_5 CO2_{it-1} + \beta_6 TECH_{it-1} + \beta_7 \overline{LGDP}_i + \beta_8 \overline{KOF}_i + \beta_9 \overline{RENE}_i + \beta_{10} \overline{URB}_i \\ & + \beta_{11} \overline{CO2}_i + \beta_{12} \overline{TECH}_i + u_{it}\end{aligned} \tag{3}$$

4. Results and discussion

This section starts with data descriptives and background tests to lead to the estimation of the regression method.

Table 2 provides the descriptive statistics of the included variables. Here, one can see that variables like EPI, LGDP, and KOF, are under-dispersed[1] while RENE, CO_2, and TECH are over-dispersed.[2] Moreover, since the Jaque Bera and Shapiro-Wilk test for normality indicates that the variables are non-normal (Jarque and Bera, 1980; Shapiro and Wilk, 1972), the mixture of under and over-dispersed requires advanced panel data models to address the distribution heterogeneity.

Fig. 1 also added to this distribution heterogeneity evidence that the correlation among the variables with the dependent variable does vary because of changes in the distribution position of the dependent variable. Most of the correlation patterns are inverted U-shaped, indicating that at median levels of EPI it is most strongly associated with the independent variables except for CO_2 which depicts an N-shaped pattern.

Table 3 provides the CIPS test's second-generation panel unit root test results (Pesaran, 2007). According to it, other than LGDP all the variables are insignificant at the level thus confirming that they are non-stationary. Based on the Pesaran Cross section ADF test (Pesaran, 2003), RENE is non-stationary at level. This indicates that the cointegration test followed by a restricted ECM equation must be used to confirm the non-spuriousness of long-run estimates.

Table 4 provides the selected specification's panel cross-sectional dependence and cointegration tests. Here, it can be seen that by using the Breusch Pagan LM (Baltagi et al., 2012) and Pesaran's (2014) CD test the model residuals are cross-sectionally dependent, prompting second-generation panel data models. The variables are of mixed order and have cross-sectional dependence; cointegration is needed among the variables. Table 4 provides the second-generation Westerlund (2005) panel cointegration test and Pedroni (2004) test with adjusted cross-sectional averages are significant, confirming cointegration in the specification provided in Equation (1).

Building on the pre-tests and descriptive statistics, Table 5 provides the long-run estimates of Equation (2). Here, in all percentiles, one can see that the intercept is negative, showing that all other excluded variables jointly increase ecological risk in selected countries. This increase shows the importance of selected independent variables as potential policy options to reduce ecological risk. For the case of the 25th percentile the independent variables explain 46% of changes in the dependent variable. For the case of median, the independent variables explain 65% of changes in the dependent variable and for the case of the 75th percentile the independent variables explain 51% of changes in the dependent variable. Lastly, the overall Wald test is significant confirming that models are fit.

While discussing the effects of renewable energy in Tables 5 and it leads to a decrease in the ecological risk for all percentiles and it is most effective at the median of environmental performance. The quantile-wise/distribution asymmetric changes in the long-run effects are also visualized in Fig. 2. A study by Abbas et al. (2021) showed that an increase in the proportion of clean energy leads to improved environmental performance.

In the case of environmental pollution, an increase of CO_2 emissions increases ecological risk at all percentiles and it is most harmful in the case of highly environmentally performing (low ecological risk) countries. The quantile-wise/distribution asymmetric changes in the long-run effects are also visualized in Fig. 2. Many studies have asserted this effect (Doney et al., 2012; Zhang et al., 2012).

Globalization has shown to be ecological performance promoting at all percentiles. It is highly effective in the case of high ecological risk. The quantile-wise/distribution asymmetric changes in the long-run effects are also visualized in Fig. 2. These results are similar to Ebrahimi et al. (2021) and Wang et al. (2021) and the major reason is the self-regulation promoted because of globalization (Christmann and Taylor, 2001; Zhu and Sarkis, 2004).

Results showed that increased GDP and green technology did not significantly affect the ecological risk. The quantile-wise/distribution asymmetric changes in the long-run effects are also visualized in Fig. 2. The GDP results are similar to Yang et al. (2012). The primary reason for insignificance is the equal incidence of substitution and scale effects of GDP. The insignificance of green technology is also supported by Ma et al. (2020) whereby technological innovation does not necessarily mitigate all forms of pollution.

While discussing the dependence effects, national averages of renewable energy and globalization have negative and positive spillover effects on environmental performance respectively. Studies like Strassburg et al. (2018) and Tittensor et al. (2014) have discussed the potential biodiversity-deterring effect of renewable energy. Studies like Zahid et al. (2020) pointed out that during the phase of renewable energy infrastructure development there are some environmental effects because of logistics and construction processes.

Table 6 uses Equation (3) to form an ECM equation estimating short run coefficient, convergence coefficient, independent variable multipliers, and cross-sectional dependence multipliers. In the short run, the intercept is negative for the 25th and 50th percentiles indicating that other excluded variables hinder environmental performance in the short run.

CO_2, LGDP, and KOF contribute to ecological risk in the short run while RENE reduces ecological risk. The effects of CO_2 are well documented in the literature. The effect of LGDP and KOF is noticeable from the fact that it takes time for the responsible activities to create a change. It is discussed under the environmental Kuznets curve (EKC) hypothesis.

While assessing the convergence coefficients are shown in Fig. 3. These coefficients are negative and significant at the 25th and 50th percentiles, with the highest effect at the 25th percentile and insignificant at the 75th percentile. This means the proposed model has the highest convergence speed/effectiveness for highly ecologically risky regions/periods while these policy options have diminishing returns which leads to its ineffectiveness in the long run for the case of low ecologically risky regions.

The multiplier effect of independent variables is shown with 'L.' as a prefix. They are the long-run effects adjusted for the convergence coefficient. It represents how much the dependent variable would change for one unit change in the independent variable in one time period. Here, signs are to be inverted as current signs show the movement of the dependent variable to rectify disequilibrium. It is shown that LGDP has a negative multiplier effect in disequilibrium correction while KOF and TECH have a positive multiplier in disequilibrium correction from environmental performance. Average GDP is positive while average KOF has a negative multiplier effect on environmental performance in the

[1] Means are higher than standard deviations.
[2] Means are lower than standard deviations.

Table 2
Descriptive statistics for selected variables.

Variables	EPI	LGDP	KOF	RENE	CO_2	TECH
Obs.	1366	1366	1366	1366	1366	1366
Mean	42.139	9.305	68.311	10.869	0.924	288.842
Std. dev.	12.653	1.217	14.191	13.589	0.942	10306.8
Skewness	0.127	−0.301	−0.412	1.995	2.862	5.747
Kurtosis	−0.751	−0.959	−0.733	4.437	1.018	34.987
JB Test	34.601	63.657	57.191	6723.6	545.63	148.93
Prob. (JB)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
S-Wilk	0.974	0.951	0.961	0.758	0.703	0.286
Prob (S-Wilk)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

*Significant at 10%. **significant at 5%. ***Significant at 1%.

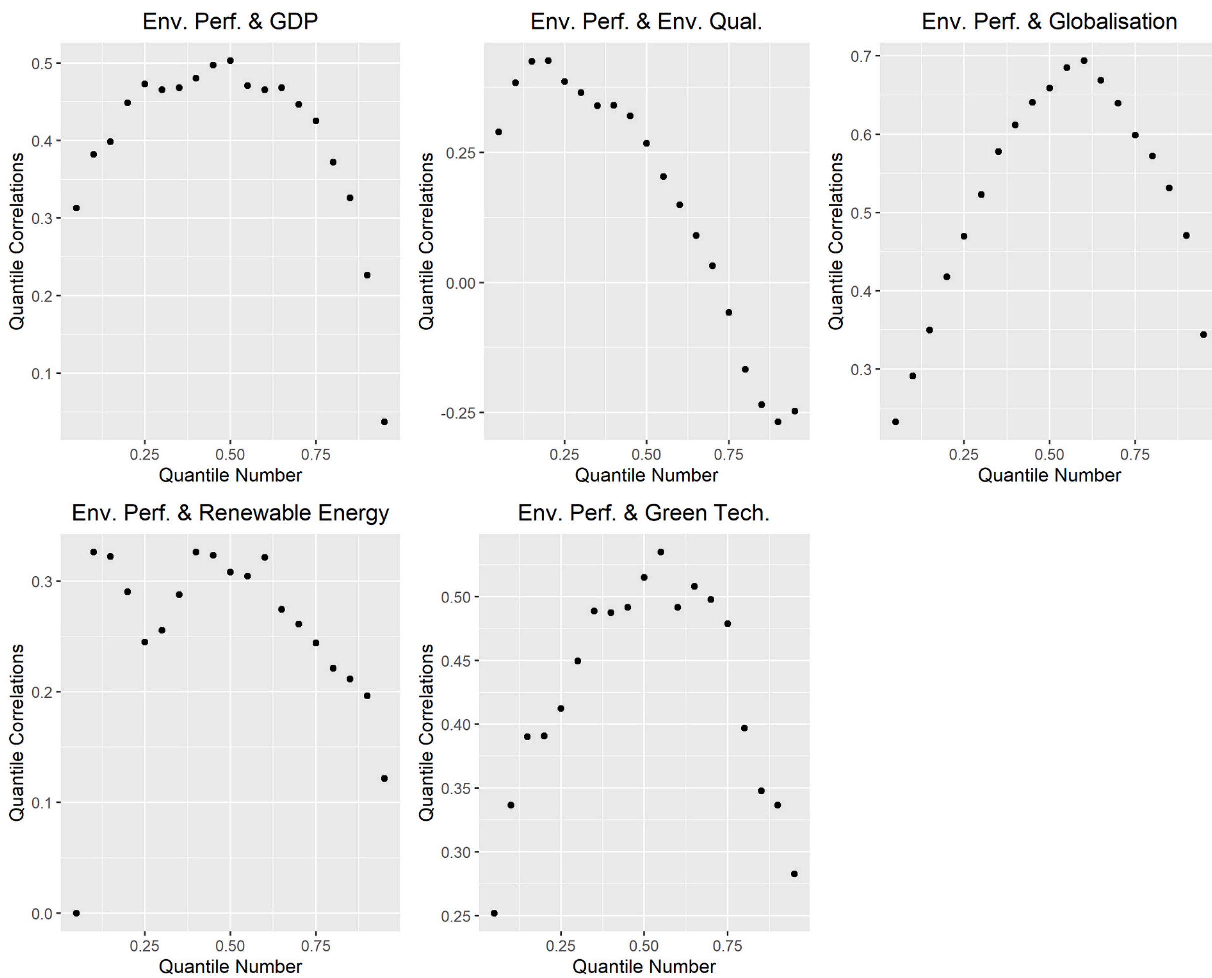

Fig. 1. Distribution asymmetric correlation plots.

Table 3
Second Gen. Panel unit root tests.

Variable	CIPS Test (Prob)	Pesaran ADF (Prob)
EPI	−1.618 (0.100)	−2.043 (0.00)**
CO_2	−0.645 (0.100)	−2.385 (0.00)**
LGDP	−2.132 (0.017)**	–
KOF	−1.951 (0.100)	−9.981 (0.00)**
TECH	−1.503 (0.100)	–
RENE	−1.507 (0.100)	−0.406 (0.342)

* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 4
Cross-sectional dependence and cointegration tests.

Test	Test Statistic	Prob.
Breusch-Pagan LM Test	9293.9	0.000[b]
Pesaran CD Test	11.642	0.000[b]
Westerlund Variance Ratio Cointegration Test	−1.351	0.094[a]
Pedroni Modified PP Cointegration Test	7.857	0.000[b]
Pedroni PP Cointegration Test	4.427	0.000[b]
Pedroni ADF Cointegration Test	5.125	0.000[b]

[a] Significant at 10%, **significant at 5%.
[b] Significant at 1%.

Table 5
Long run CCEMG quantile regression.

Variables	At 25th Percentile Coef. (Prob).	At 50th Percentile Coef. (Prob).	At 75th Percentile Coef. (Prob).
Cons.	−17.883 (0.000)[c]	−0.151 (0.023)[b]	−15.810 (0.032)[b]
RENE	0.636 (0.000)[c]	0.803 (0.000)[c]	0.754 (0.000)[c]
CO_2	−2.229 (0.443)	−4.100 (0.016)[b]	−6.519 (0.045)[b]
LGDP	−0.589 (0.805)	0.286 (0.928)	−0.803 (0.827)
KOF	0.329 (0.000)[c]	0.250 (0.012)[b]	0.223 (0.088)[a]
TECH	−0.001 (0.761)	−0.0005 (0.897)	−0.0001 (0.964)
RENE_AVG	−0.688 (0.000)[c]	−0.836 (0.000)[c]	−0.788 (0.000)[c]
CO_2_AVG	−2.412 (0.396)	−0.002 (0.999)	2.544 (0.502)
LGDP_AVG	2.628 (0.388)	1.689 (0.662)	3.344 (0.436)
KOF_AVG	0.296 (0.052)[a]	0.364 (0.025)[b]	0.362 (0.051)[a]
TECH_AVG	0.002 (0.586)	0.001 (0.646)	0.001 (0.739)
R squared	0.458	0.652	0.513
Wald (Prob)	86121.46 (0.000)[c]	57404.09 (0.000)[c]	52675.22 (0.000)[c]

[a] Significant at 10%.
[b] Significant at 5%.
[c] Significant at 1%.

selected countries.

5. Conclusion

Ecological risks include climate change, biodiversity loss, deforestation, and water and waste pollution. These risks contribute to colossal costs in sustaining the standard of living. In pursuit of mitigating and abating the ecological risk there is a need for strong evasive action at national level. This study used the multidimensional ecological risk assessment using the Environmental Performance Index, enabling countries to assess changes in their habitat, environment, and biodiversity quality. Depreciation of ecological habitat diversity would greatly influence the standard of living from multiple dimensions discussed in the literature (Dasgupta and Levin, 2023; Hedin et al., 2022).

In an effort to understand long run and robust estimates of ecological risk, this study explored 55 countries for ecological risk management. The literature and theoretical review have led to the utilization of indicators like renewable energy (as clean energy), environmental pressure, GDP (as economic activity), economic and financial globalization, and green technology. All of these indicators are either direct human actions or consequences of human actions. Further, the ecological stock of the country does depend on the neighboring countries and this spillover effect is confirmed using the cross-sectional dependence tests. This study developed second generation panel data model that makes regression estimates robust to cross-sectional dependence.

Building on debates and estimation models in previous studies, this study used a novel estimation model by integrating two approaches. The first approach is the regression algorithm named Quantile regression. The second approach is the regression specification named CCEMG and DFE. The hybrid model used by the study has an inbuilt capacity to address several post-regression issues like unobserved heterogeneity, non-normal variables, time-series autocorrelation, and cross-sectional dependence.

The panel data estimation results showed that renewable energy, CO_2 emissions, and globalization are the major factors determining the ecological risks in the long run at medians. While economic activity and

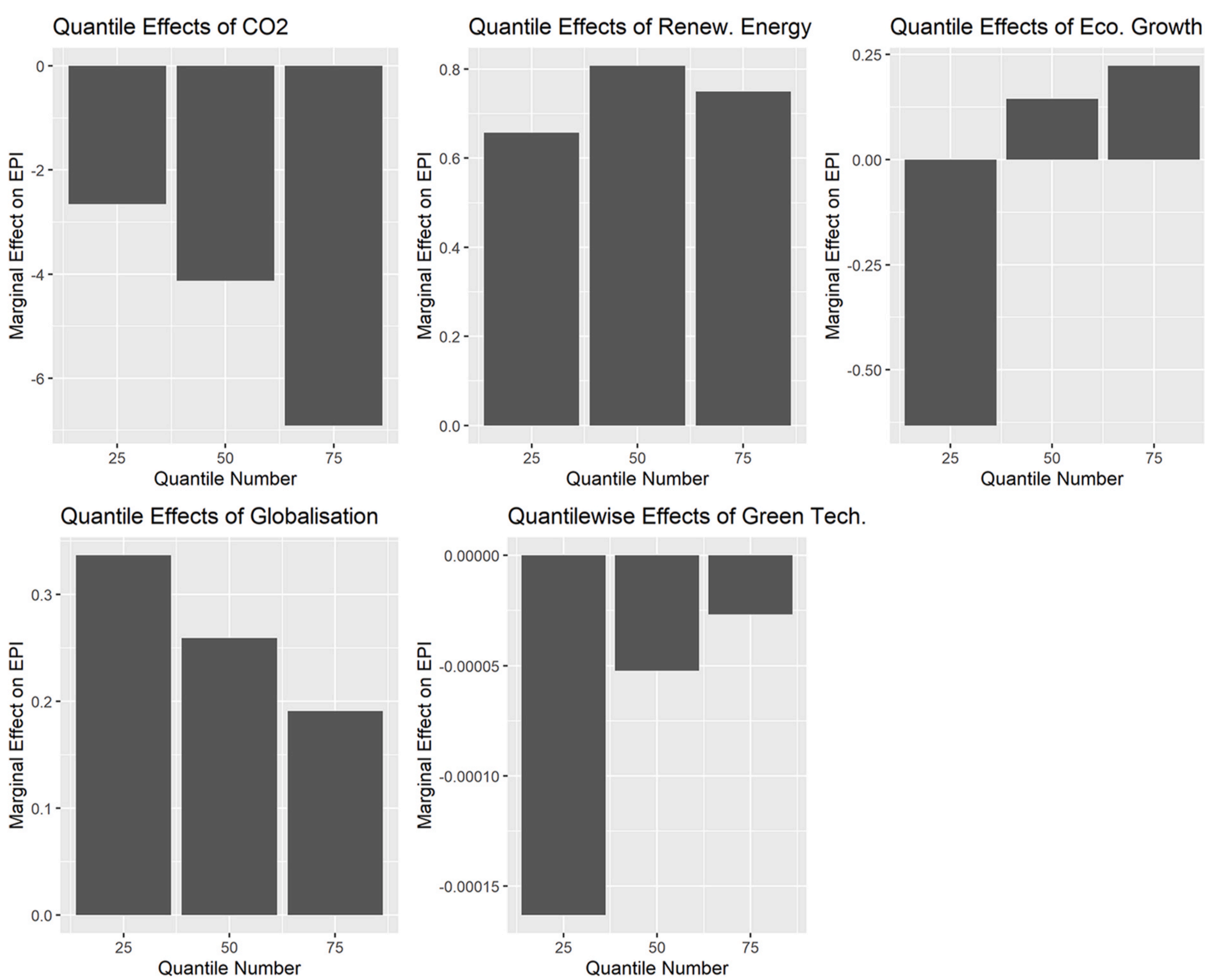

Fig. 2. Distribution asymmetric long run effects.

Table 6
CCEMG quantile regression with ECM specification.

	At 25th Percentile	At 50th Percentile	At 75th Percentile
	Coef. (Prob).	Coef. (Prob).	Coef. (Prob).
Const.	−1.973 (0.000)[c]	−0.821 (0.003)[c]	0.727 (0.248)
D.RENE	0.144 (0.000)[c]	0.129 (0.000)[c]	0.120 (0.001)[c]
D.CO_2	−0.802 (0.129)	−0.854 (0.079)[a]	−0.816 (0.484)
D.LGDP	−2.917 (0.036)[b]	−3.317 (0.002)[c]	−3.223 (0.050)[b]
D.KOF	−0.058 (0.027)[b]	−0.007 (0.726)	−0.022 (0.555)
D.TECH	0.000 (0.924)	0.000 (0.919)	0.000 (0.216)
L.EPI	−0.022 (0.000)[c]	−0.006 (0.056)[b]	0.006 (0.334)
L.RENE	0.009 (0.527)	0.004 (0.821)	0.012 (0.633)
L.CO_2	0.052 (0.866)	0.012 (0.935)	−0.063 (0.781)
L.LGDP	−0.629 (0.074)[a]	−0.531 (0.023)[b]	−0.510 (0.161)
L.KOF	−0.003 (0.802)	0.023 (0.004)[c]	0.050 (0.000)[c]
L.TECH	0.000 (0.768)	0.000 (0.597)	0.000 (0.066)[a]
L.RENE_AVG	−0.009 (0.490)	−0.003 (0.841)	−0.010 (0.714)
L.CO_2_AVG	−0.284 (0.374)	−0.136 (0.417)	0.102 (0.712)
L.LGDP_AVG	0.899 (0.011)[b]	0.698 (0.009)[c]	0.464 (0.205)
L.KOF_AVG	0.009 (0.473)	−0.022 (0.024)[b]	−0.043 (0.001)[c]
L.TECH_AVG	0.000 (0.720)	0.000 (0.802)	0.000 (0.177)

[a] Significant at 10%.
[b] Significant at 5%.
[c] Significant at 1%.

green technology do not have effect on ecological risks, results implicate that excessive emissions could lead to feedback loops leading to global warming (Lu et al., 2018). It is not only the environmental pollution that is affected; emissions do tend to destroy other habitats and shrink the biodiversity. Globalization has shown a sustainability promoting effect (Kolk et al., 2008). Economic and financial integration across countries helps them to learn and support each other to develop biodiversity as the most important public good. At the same time, GDP plays a role in the short run which is opposed to the empirical study like Wang et al. (2020). Changes in economic activity, if not catered for ecological footprints, do tend to destroy biodiversity. Policy interventions are much needed in this case in order to make economic activity greener as discussed EKC hypothesis.

The cross-section averages absorb the spillover effect as suggested by the CCEMG model. Surprisingly, the incorporated spillover/dependence effects showed that high averages of renewable energy hinder environmental performance while high averages of globalization contribute as a multiplier on environmental performance. The average is negative showing that this negative effect is not a local effect but rather it is a cross-country effect (negative spillover effect). Infrastructure development may force the habitat to migrate across regions and countries, disturbing their habitat balance. In this case, globalization positive spillover effect can be used to form intergovernmental collaborations to support vulnerable habitats and ecosystems.

5.1. *Limitations of the study and future research*

The study outcomes are limited to the DFE specification, assuming that the long and short-run effects are homogenous across countries hence these results are assuming that there is long run slope homogeneity. Future studies can firstly explore the quantile-based slope heterogeneity test and develop the model using MG and PMG specifications to allow for slope heterogeneity and expand the model to subindices of the environmental performance index. Secondly, future studies can also explore the strategies for mitigating ecological risk in the low-risk regions which this study is unable to do. Lastly spatial models can be used to assess the climate change spill over effects across countries.

Ethical approval

The entire research process is in line with our institutional research

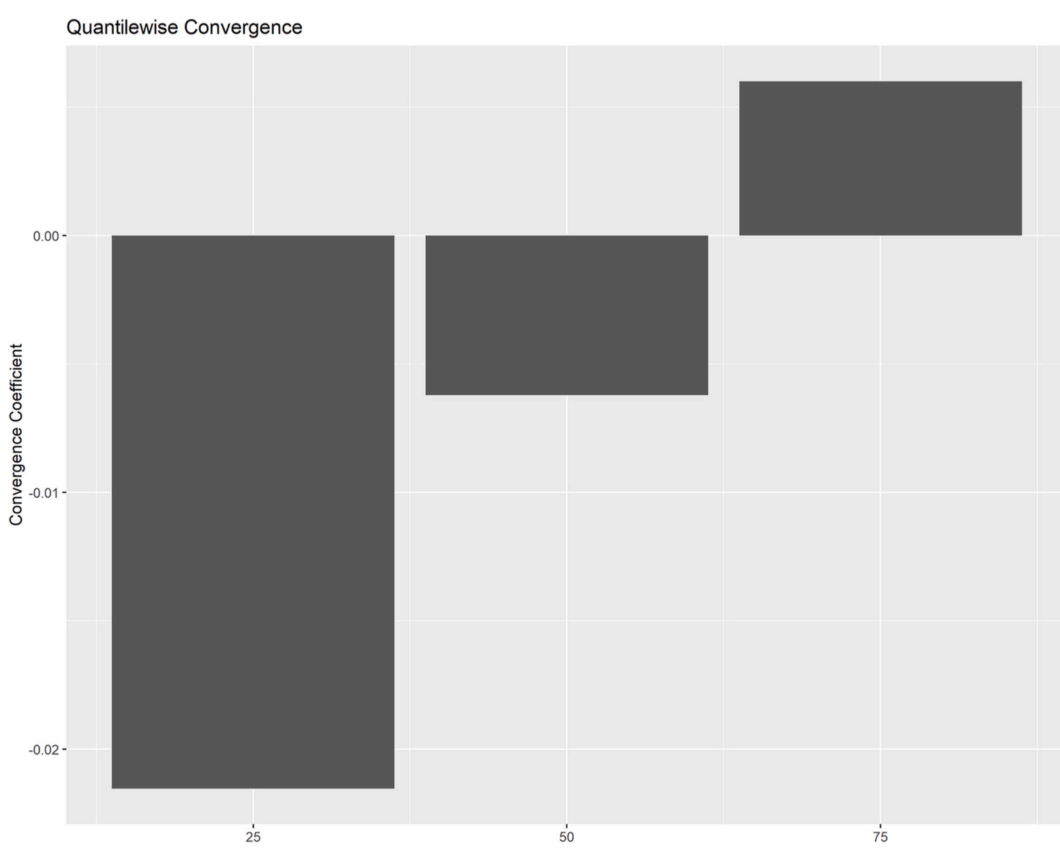

Fig. 3. Distribution asymmetric convergence coefficient.

ethics policy. We declare that all ethical standards are met and complied with in true letter and spirit.

Informed consent

All participants in this study volunteered themselves during the entire research process, and their consent was taken at inception.

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CRediT authorship contribution statement

Shajara Ul-Durar: Writing – original draft, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Noman Arshed:** Methodology, Formal analysis, Data curation. **Marco De Sisto:** Writing – original draft, Supervision, Investigation. **Alireza Nazarian:** Writing – original draft, Supervision, Conceptualization. **Ashina Sadaf:** Writing – original draft, Software, Methodology, Formal analysis.

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.

Appendix

Table 7
Sample Countries

Algeria	Denmark	Kazakhstan	Poland
Argentina	Ecuador	Kuwait	Qatar
Australia	Estonia	Lithuania	Romania
Austria	France	Malaysia	Saudi Arabia
Azerbaijan	Germany	Mexico	Slovenia
Bangladesh	Greece	Morocco	Spain
Belarus	Hungary	Netherlands	Sweden
Belgium	India	New Zealand	Thailand
Brazil	Indonesia	North Macedonia	Turkmenistan
Bulgaria	Iraq	Norway	Ukraine
Canada	Ireland	Oman	UAE
Chile	Israel	Pakistan	UK
Colombia	Italy	Peru	Uzbekistan
Croatia	Japan	Philippines	

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