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## Does digitalization lead to climate awareness? A cross-country panel data analysis

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# DOES DIGITALIZATION LEAD TO CLIMATE AWARENESS?

A CROSS-COUNTRY PANEL DATA ANALYSIS

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Donghyun Park, and John Beirne*

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## ABSTRACT

Climate change, currently one of the most pressing challenges, requires increased public awareness and decisive action to support effective mitigation efforts. Comprehending digitalization's potential role in shaping public understanding of climate-related issues has become a progressively important area of study. Against this backdrop, we undertake a pioneering attempt to examine how digitalization influences climate change awareness across diverse countries. To capture the multifaceted nature of digitalization, we construct a digitalization index, applying principal component analysis. Leveraging an annual panel dataset encompassing 65 countries over 2005–2020, our study applies several econometric techniques: panel-corrected standard errors, feasible generalized least squares, two-step system generalized method of moments, and panel quantile regression, to investigate this nexus. Our findings unveil a nonlinear U-shaped relationship between digitalization and climate awareness, suggesting that digitalization initially has a negligible or adverse impact but substantially boosts climate awareness after a digital maturity threshold is achieved. Furthermore, the share of renewable energy consumption also follows a U-shaped nonlinear pattern, while household consumption and corruption control contribute to boosting climate awareness. Conversely, the impact of human development, gross fixed capital, and trade openness becomes negligible when endogeneity is controlled. Our quantile-based analysis further validates these conclusions, although some factors vary across quantiles. These findings carry important policy implications, particularly emphasizing targeted fiscal policies to strengthen digital infrastructure and climate communication efforts, thereby facilitating tailored strategies for improved public climate awareness to meet climate sustainability.

**Keywords:** digitalization, climate awareness, panel data analysis, nonlinear relationship

**JEL codes:** C33, O11, Q01, Q54

## 1. INTRODUCTION

Climate change casts a long shadow over the 21st century, posing serious threats to natural ecosystems and human societies. In recent years, the world has experienced an increasing number of climate-related disruptions, such as extreme weather events, rising global temperatures, and changes in biodiversity. These shifts have far-reaching economic, social, and environmental implications (IPCC, 2022). The Intergovernmental Panel on Climate Change (IPCC) emphasizes the urgency of immediate and significant reductions in greenhouse gas emissions to curb these escalating risks and safeguard the planet for future generations. Consequently, transitioning to a low-carbon economy has become a paramount goal for nations worldwide, as evidenced by commitments made at the 26th Conference of the Parties (COP26) climate summit (Shahbaz et al., 2022). Effective policy action hinges on robust climate policies coupled with widespread public support (Lee et al., 2015; Chen et al., 2019; IPCC, 2022). While the scientific consensus on climate change is substantial, translating this knowledge into broad public awareness and support for mitigation efforts remains a complex challenge (Lee et al., 2015). Therefore, it is crucial to understand the key factors that drive climate change consciousness.

This study delves into the potential role of digitalization—a broad and evolving phenomenon encompassing internet access, mobile technologies, and digital communication platforms—in shaping public awareness and understanding of climate change. Digitalization has a vast potential to transform how climate-related information is shared and consumed by facilitating access to information, enabling real time communication, spreading information rapidly and widely, and supporting data driven decision-making (Lee et al., 2015; Charfeddine and Umlai, 2023). The recent surge of digital platforms, such as social media, online news outlets, and educational websites, offers unprecedented opportunities to raise awareness about complex climate change issues, engage diverse audiences, and foster a global discourse on climate challenges (Charfeddine and Umlai, 2023). However, an empirical question remains: *to what extent does digitalization translate into increased climate change awareness?*

As discussed in the literature review (Section 2), previous research has primarily focused on environmental awareness as a precursor to climate change awareness and attempted to uncover individuals' environmental perceptions, often relying on survey data and microlevel analysis (Calculli et al., 2021). Such studies highlight the role of educational initiatives and increased environmental knowledge in improving public attitudes toward environmental preservation (Uzunboyulu et al., 2009; Despotovic et al., 2021). However, research explicitly

investigating climate change awareness is a more recent development. Early studies have identified basic education, climate literacy, income levels, and socioeconomic development as critical drivers of climate change awareness (Lee et al., 2015; Lucas et al., 2021). Other factors like renewable energy usage (Lucas et al., 2021), the Human Development Index (HDI) (Opoku et al., 2022), gross fixed capital formation (GFCF) (Meng et al., 2022; Li et al., 2023), household consumption patterns (Ricci and Banterle, 2020), corruption control (Usman et al., 2022; Sahoo et al., 2023), and trade globalization (Peters and Hertwich, 2008) may have also been linked to climate change awareness either directly or indirectly, although revealing conflicting findings. While these studies offer valuable insights, they often rely on survey-based methodologies and limited geographical scope, impeding a comprehensive understanding of the complex dynamics at play. Generalizing findings across diverse geographical, economic, and cultural regions requires comprehensive cross-country data analysis. Additionally, some studies report conflicting outcomes regarding several determinants of climate change awareness (literature review).

Furthermore, the burgeoning role of digitalization in shaping public opinion and behavior in the context of climate change awareness has received scant to no attention. Existing research also often employs narrow proxies for digitalization, such as internet usage, broadband access, or mobile subscriptions, and tends to rely on survey-based methodologies that may not fully capture the complexity of digital influences. Additionally, most previous studies utilize linear models, whereas macroeconomic data may exhibit relationships across different market circumstances.

In light of these gaps, our study intends to explore the impact of digitalization on climate change awareness across diverse countries. Additionally, we account for several critical factors as control variables based on existing literature to assess their influence on climate awareness. The Notre Dame Global Adaptation Initiative (ND-GAIN) climate readiness score (CRS) is employed as a proxy for climate awareness because, while climate readiness and awareness are distinct in their definitions, they share several overlapping components that closely interlink them. Climate readiness refers to a country's ability to leverage investments and convert them into adaptive actions, while climate awareness involves understanding the causes, consequences, and mitigation strategies related to climate change (Azócar et al., 2021; ND-GAIN, 2023). Empirical studies have established that heightened climate awareness directly contributes to enhanced climate preparedness and readiness (e.g., Marshall et al., 2013; Arıkan and Günay, 2021; Epule et al., 2021; Yao et al., 2024). For instance, Arıkan and Günay (2021) emphasize that awareness of climate risks fosters higher adaptive capacities and drives more proactive policy

responses—key components of readiness. Moreover, climate awareness inherently involves disseminating knowledge regarding climate change’s causes and effects alongside promoting mitigation and adaptation strategies (Azócar et al., 2021). These knowledge components are integral to readiness, as individuals and communities must be aware of climate risks before they can take action to build resilience and adapt effectively. As a result, higher climate awareness is often a precursor to greater readiness for implementing climate strategies (Epule et al., 2021). Consequently, while the terms climate readiness and awareness differ conceptually, they are strongly correlated, and their use as interchangeable terms is supported by the significant empirical linkage between the two, as demonstrated in both academic literature and real-world policy frameworks. Therefore, using the ND-GAIN CRS index as a climate awareness proxy is practical and justified.

Given the broad scope of digitalization, we have constructed a digitalization index utilizing principal component analysis (PCA) to encompass multiple digital components due to the unavailability of a country-wise digitalization index. We utilize comprehensive cross-country panel data (65 countries over 16 years) and employ a range of sophisticated econometric models, e.g., cointegration tests, panel-corrected standard errors (PCSE), feasible generalized least squares (FGLS), two-step system generalized method of moments (GMM), and panel quantile regression (QR) techniques to attain the objectives above. Our findings indicate a nonlinear U-shaped impact of digitalization on climate change awareness across all estimated models. Other factors, such as the share of renewable energy (also displaying a U-shaped nonlinear pattern), household consumption, and corruption control, also significantly promote climate change awareness. Conversely, HDI, GFCF, and trade openness show a significant positive effect on climate awareness, based on static models (PCSE and FGLS). However, their impacts become negligible when endogeneity is controlled under the GMM framework. Our findings are consistent and robust, as validated by several estimators.

Our study makes several vital contributions to the prevailing literature. Firstly, it pioneers the examination of digitalization’s impact on climate change awareness across diverse countries, enhancing our understanding of technology’s role in shaping public opinion on this critical issue. Additionally, we incorporate a wide range of economic, social, and environmental variables as controls to provide a holistic understanding of the determinants of climate change awareness. Secondly, contrasting previous studies that have focused on single indicators of digitalization, our research constructs a digitalization index to cover a broad range of digital tools and platforms, including individual internet usage, broadband subscriptions, mobile cellular subscriptions, and

information and communications technology (ICT) goods imports and exports, providing a more comprehensive view of how digitalization impacts climate change awareness.

Thirdly, methodologically, unlike previous research that has often relied on qualitative and survey-based data, which may be subject to biases and limitations in generalizability, our study overcomes these limitations by using comprehensive cross-country panel data and advanced analytical techniques, blending mean-based, dynamic, and quantile-based approaches, to provide more accurate and robust insights into the impact of digitalization on climate change awareness. To be specific, our baseline model, PCSE, is capable of addressing several critical data issues—cross-sectional dependence, heteroscedasticity, serial correlation, and non-normality—and is particularly useful in small samples when time is less than cross-sectional units, as in our case. The FGLS technique is used to ensure the robustness of our baseline estimates. We use a two-step GMM approach to handle potential endogeneity and further verify the robustness of our baseline findings, which is well suited for dynamic panel datasets where the dependent variable is persistent and explanatory factors may be endogenous. Unlike previous literature, we have also employed the bootstrapped panel QR approach to see the results across different market states. This approach can address potential distributional heterogeneity associated with panel data and is suitable when the sample size is small (i.e.,  $T < N$ ). Lastly, our analysis underscores the existence of nonlinear dynamics, especially regarding the impact of digitalization and renewable energy on awareness, while also stressing the significance of governance, household consumption, and developmental factors. These findings provide valuable insights for policymakers utilizing digital technologies and macroeconomic factors to improve climate change awareness and support mitigation efforts.

The remainder of the paper is designed as follows: Section 2 reviews the pertinent literature, Section 3 highlights the stylized facts of variables, Section 4 outlines the data and methodology employed. The empirical results and discussion are presented in Section 5, and finally, Section 6 wraps up the study with practical policy insights.

## **2. LITERATURE REVIEW**

Climate change and its repercussions pose substantial economic challenges. To address the escalating climate change issues, climate policy actions accompanied by considerable public support are essential (Lee et al., 2015). Heightened environmental awareness is crucial for fostering such support (Chen et al., 2019). Consequently, climate change awareness has increasingly captured the attention of policymakers and researchers worldwide. Early research

primarily focuses on environmental awareness rather than climate awareness, often employing survey methods with microlevel data (Calculli et al., 2021). These studies aim to understand individual attitudes towards environmental issues. For instance, Uzunboylu et al. (2009) surveyed university students to assess the impact of mobile learning on environmental awareness, finding positive effects on participants' attitudes towards maintaining a clean environment and promoting environmental preservation. Similarly, Despotovic et al. (2021) surveyed 382 farmers in northern Serbia and documented that increased environmental knowledge led to greater environmental consciousness and the adoption of more sustainable practices. Salahodjaev (2018) also documented a positive link between individuals' cognitive skills and environmental awareness based on cross-country data from 119 economies.

Few studies have concentrated on climate change awareness, with most relying on survey-based methodologies similar to those used for environmental awareness. As such, Lee et al. (2015), utilizing survey data from 119 economies (Gallup World Poll, 2007–2008), identify the key drivers of climate change awareness, including basic education, climate literacy, and local temperature perceptions. Lucas et al. (2021) similarly suggest a positive impact of renewable energy consumption and public attitudes towards climate change awareness based on surveys and semistructured interviews. However, Calculli et al. (2021) report contrasting views from a survey of 1,834 respondents in Italy, highlighting a generally pessimistic outlook on environmental challenges, though younger generations expressed greater concern than older adults.

Additionally, early studies have examined some factors that may influence climate change awareness, such as HDI, sociodemographic variables, and household consumption patterns. For instance, Opoku et al. (2022) unearth that heightened HDI can promote environmental sustainability, potentially impacting climate awareness. Sociodemographic factors, including gender, age, education, ethnicity, and income, also shape climate awareness and attitudes (Masud et al., 2017). Furthermore, households' choices—such as consumption patterns, energy usage, logistics, and waste management—can impact climate change (Claudelin et al., 2020). Perhaps household consumption patterns influence climate awareness through individual behaviors (Ricci and Banterle, 2020) and levels of consumer knowledge (Marx-Pienaar and Erasmus, 2014).

Previous research has also investigated other factors—GFCF, control of corruption, and trade globalization—and linked them with environmental quality or sustainability, indirectly connecting with climate awareness. For example, Ajide and Ibrahim (2021) and Meng et al. (2022) report that GFCF can improve environmental quality by diminishing carbon emissions. On the flip

side, Li et al. (2023) observe an adverse effect of GFCF on ecological quality. Usman et al. (2022) find that control of corruption and income level escalate carbon emissions, though their interaction mitigates emissions, thereby raising environmental awareness. They rationalize that higher income levels lead governments and other stakeholders to implement stringent ecological policies, laws, and regulations, resulting in controlled corruption and heightened awareness regarding environmental sustainability and concerns. Similarly, Tabash et al. (2023) indicate that corruption control can improve environmental quality, while Sahoo et al. (2023) document a detrimental effect of corruption control on environmental quality. Additionally, while not directly linked to climate change awareness, trade globalization may impact it through emissions embodied in trade (Peters and Hertwich, 2008). In contrast, Copeland et al. (2021) argue that trade globalization might affect climate awareness by integrating trade and climate policies, with ambitious climate policies more likely to thrive in open trade systems.

Despite these insights, the potential link between digitalization and climate change awareness remains underexplored. Digitalization, as a broad concept encompassing various digital tools and platforms, could significantly influence climate change awareness by rapidly disseminating climate-related information (Lee et al., 2015). However, the focus has primarily been on the link between digitalization and environmental quality and sustainability (Charfeddine and Umlai, 2023). Here, too, findings are mixed. While some studies report a positive impact (Charfeddine and Umlai, 2023), others highlight potential drawbacks related to the energy consumption of digital tools (Ibrahim et al., 2023). Notably, Su et al. (2021) suggest a minimal negative impact of mobile cellular subscriptions on per capita carbon emissions.

From the above discussion, several critical points can be highlighted. First, while previous research investigates climate change awareness or environmental awareness and their various influencing factors, the potential linkage between digitalization and climate change awareness remains largely unexplored. Digitalization may significantly influence climate change awareness through the swift and broad communication and dissemination of critical climate-related information. Earlier studies often utilize single variables such as internet usage, broadband access, or mobile cellular subscriptions as proxies for digitalization. However, digitalization is a broad concept encompassing all forms of digital tools. Secondly, existing studies on climate change awareness primarily rely on survey methods to gauge public opinions, which can be susceptible to biases and limitations in generalizability. Though these public views provide valuable insights into individual attitudes and perceptions, they may not capture broader societal trends or the impact of structural factors like policy changes, macroeconomic conditions, or

technological advancements. Moreover, most studies focus on specific countries or regions. Limited studies have addressed the endogeneity issue that often arises in cross-country panel data. Failing to address it may lead to inconsistent results. Utilizing cross-country panel data accompanied by advanced econometric approaches can provide more accurate and valuable insights into how various factors, such as digitalization, influence climate awareness across different contexts and cultures.

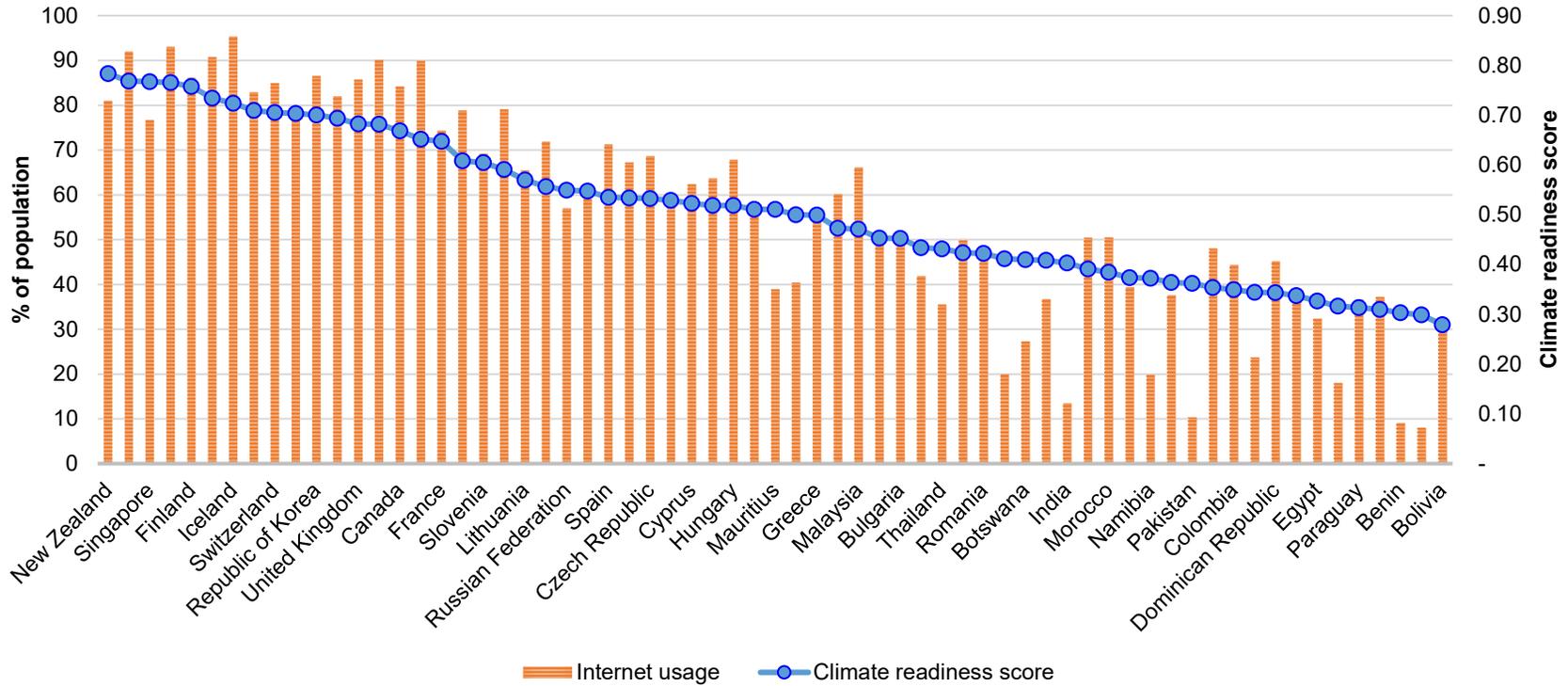
Lastly, most earlier studies are qualitative, with some adopting empirical analysis but lacking quantile-based techniques. However, economic data often suggests nonlinear relationships due to structural breaks or economic cycles. Our study attempts to lessen these gaps by investigating the impact of digitalization on climate change awareness, employing sophisticated econometric methodologies, including a quantile-based approach, on comprehensive cross-country panel data.

### **3. STYLIZED FACTS OF CLIMATE CHANGE AWARENESS AND ITS VARIOUS POTENTIAL DRIVERS**

This section provides a pictorial and analytical examination of climate change awareness and its key determinants across the 65 countries under investigation. By utilizing 16-year mean values (2005–2020) of the variables under investigation, we offer a preliminary overview of the potential nexus between climate change awareness and different factors. For Figures 1 to 9, the primary axis (left side) displays the mean values of explanatory variables, while the secondary axis (right side) shows the mean values of the dependent variable, with CRS serving as a proxy for climate change awareness.

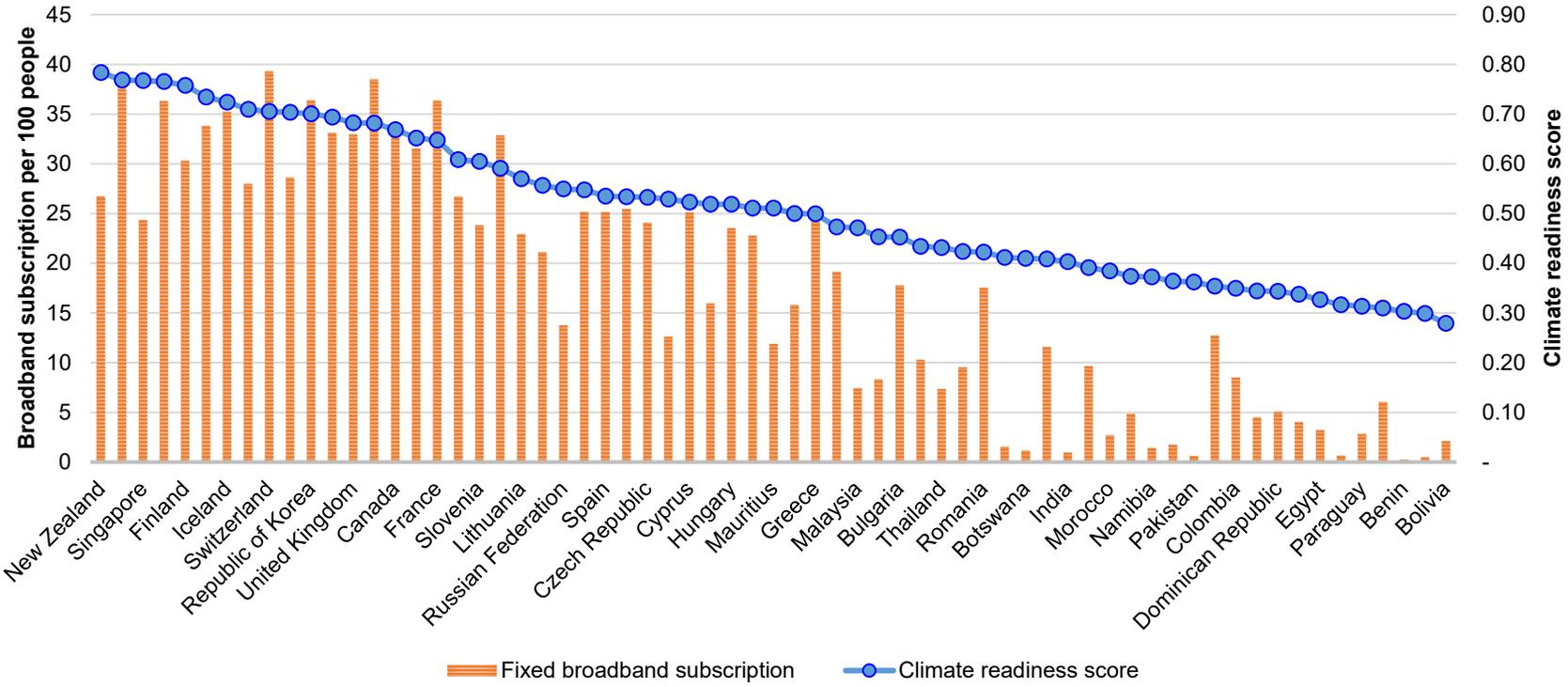
Figures 1 to 3 illustrate the relationship between digital communication platforms—internet usage, fixed broadband, and mobile cellular subscriptions—and climate change awareness. The figures reveal a positive correlation between these digital platforms and climate awareness, though the alignment is more pronounced in developed countries. Developing countries, despite the lower utilization of these platforms, exhibit lagging climate awareness. Interestingly, while fixed broadband is less prevalent, particularly in developing nations, some countries with high mobile cellular subscriptions have not yet achieved high levels of climate awareness, suggesting that mobile internet usage alone may not significantly boost climate awareness.

**Figure 1: Internet Usage and Climate Awareness**



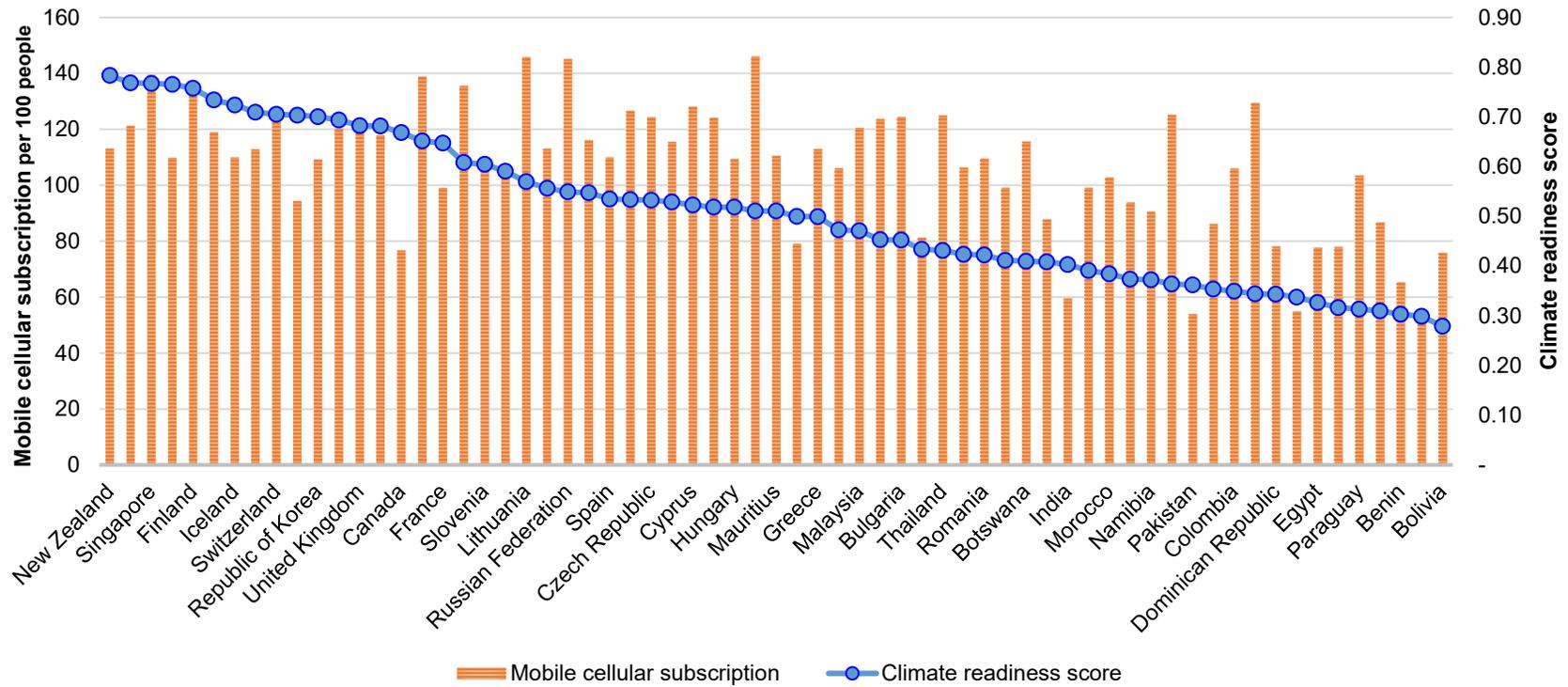
Source: International Telecommunication Union. ITU DataHub. <https://datahub.itu.int/> (accessed 30 June 2025); Notre Dame Global Adaptation Initiative Country Index (ND-GAIN). 2025. University of Notre Dame.

Figure 2: Fixed Broadband Subscription and Climate Awareness



Source: International Telecommunication Union. ITU DataHub. <https://datahub.itu.int/> (accessed 30 June 2025); Notre Dame Global Adaptation Initiative Country Index (ND-GAIN). 2025. University of Notre Dame.

Figure 3: Mobile Cellular Subscription and Climate Awareness



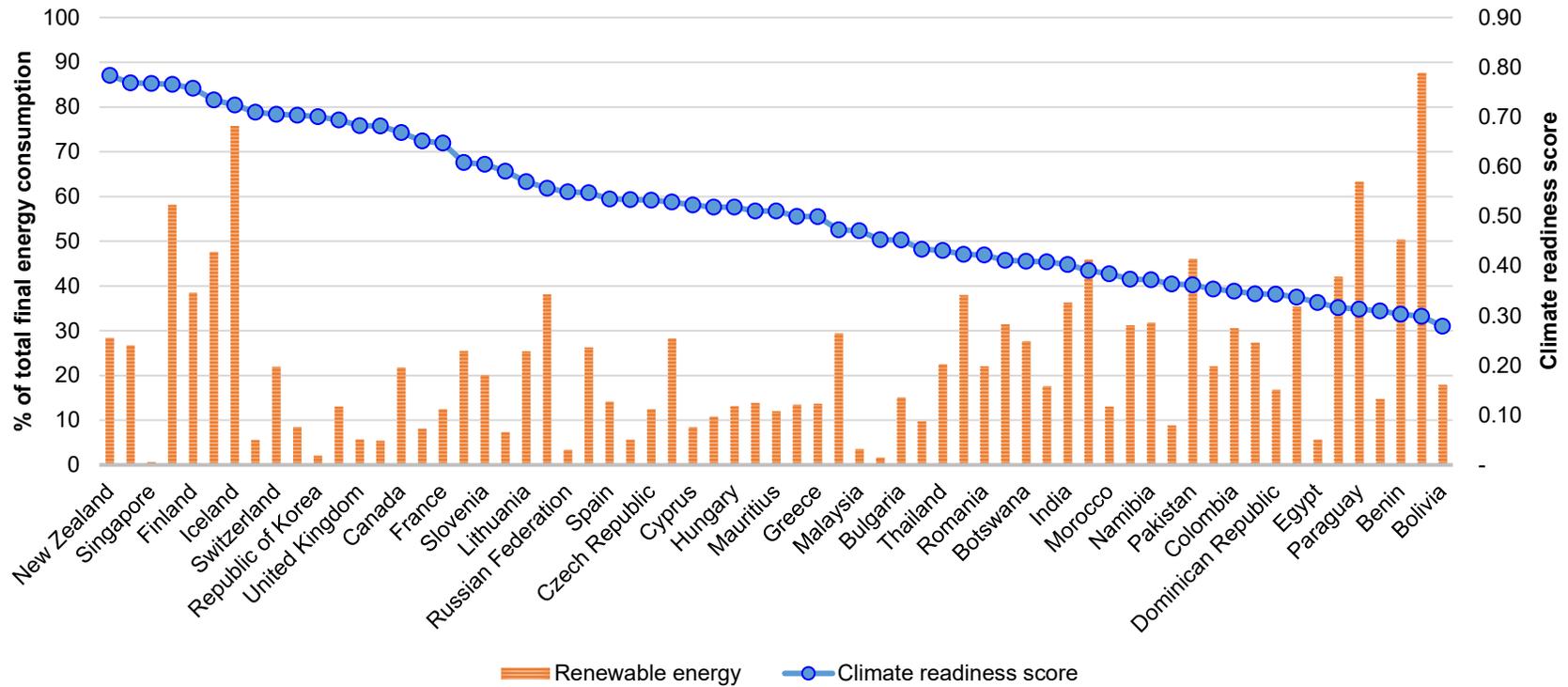
Source: International Telecommunication Union. ITU DataHub. <https://datahub.itu.int/> (accessed 30 June 2025); Notre Dame Global Adaptation Initiative Country Index (ND-GAIN). 2025. University of Notre Dame.

The relationship between renewable energy consumption and climate awareness is tricky (Figure 4). While intuitively expected to be positive, the data reveal inconsistencies. Some developed countries with high industrial activity often exhibit lower renewable energy consumption compared to their developing counterparts, while some developing countries, such as Tanzania and Paraguay, with significant renewable energy shares, demonstrate low climate awareness. Figure 5 highlights that many countries' HDIs stand tall regardless of their climate change awareness. It is also observed that highly developed countries typically demonstrate strong climate awareness, as indicated by high CRS scores. However, a notable disparity emerges in developing countries, where high HDI values do not always translate into high climate awareness scores.

Regardless of their economic and climate awareness strata, all the countries in our scope demonstrate a steady measurement of GFCF (Figure 6), i.e., growing through reinvestment is a usual phenomenon to them. Nonetheless, two countries stand out in this graph as outliers—the People's Republic of China (PRC) and Tanzania—investing substantially in their transport facilities, signifying that this investment strategy may boost economic growth but does not necessarily correlate with increased climate awareness (AfDB, 2018; Ansar et al., 2016). Strikingly, household consumption (HC) exhibits a contrasting pattern (Figure 7). Developed countries with higher climate awareness tend to have lower HC levels, while developing countries often show the opposite trend. The PRC's significant HC surge between 2005 and 2010 further emphasizes this dichotomy.

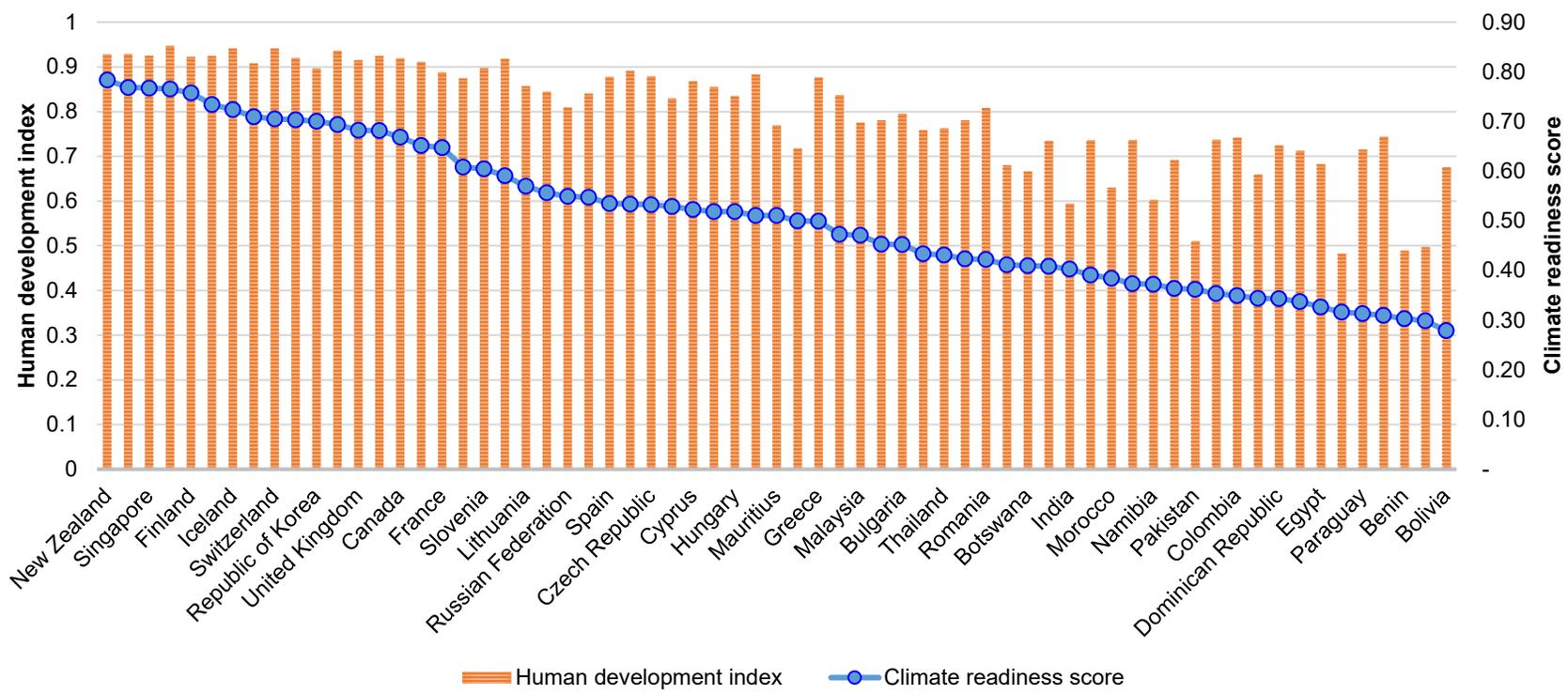
Moreover, Figure 8 highlights a positive correlation between corruption control and climate change awareness, indicating that countries with better governance tend to have higher levels of climate change awareness and vice versa. Interestingly, Russia and the Republic of Korea exhibit a moderate scale of climate awareness even if their corruption control is inferior, suggesting that other factors may influence their climate awareness. Finally, Figure 9 largely indicates a positive link between trade globalization and climate awareness across all countries. Developed countries tend to show higher levels of trade globalization and climate change awareness than developing countries. However, some countries with high trade openness still exhibit moderate climate awareness, indicating a nuanced interplay between globalization and climate change awareness.

Figure 4: Renewable Energy Consumption and Climate Awareness



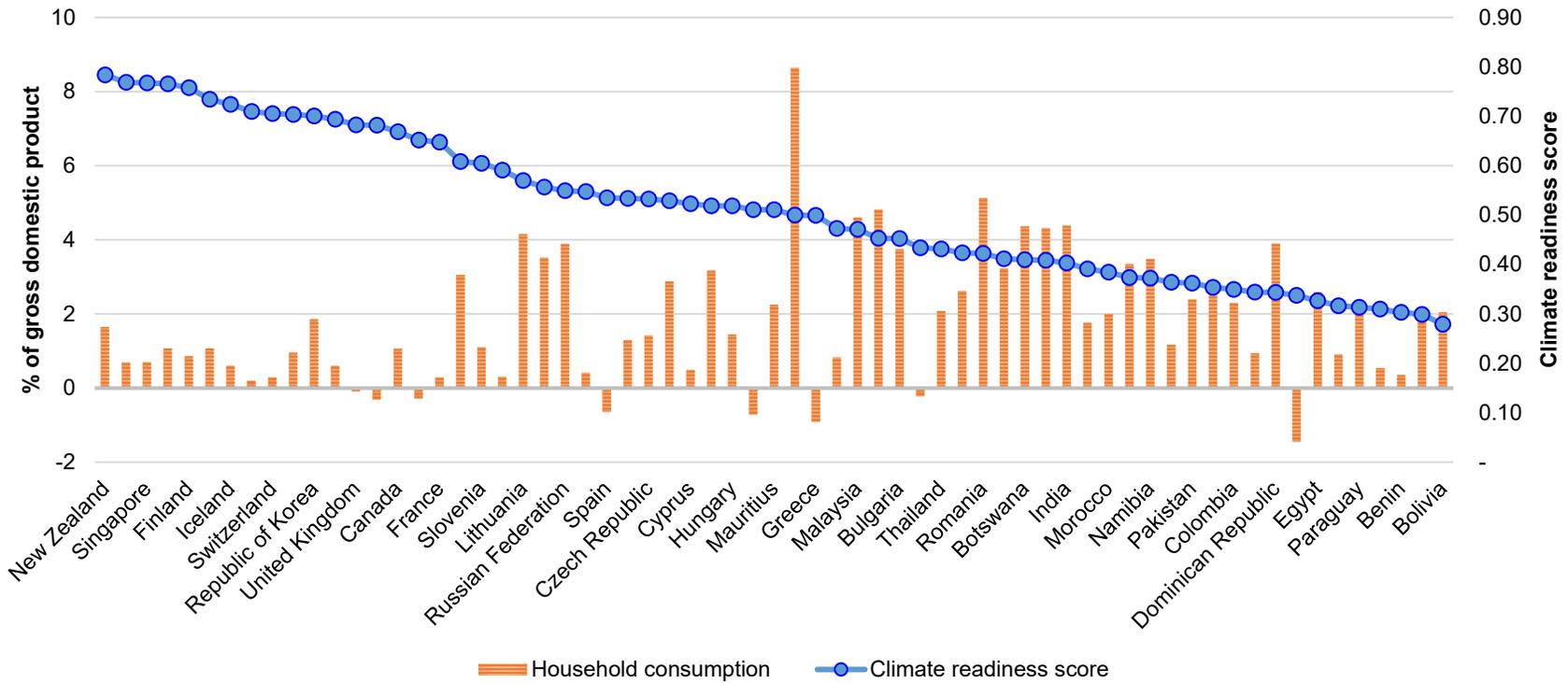
Source: International Telecommunication Union. ITU DataHub. <https://datahub.itu.int/> (accessed 30 June 2025); Notre Dame Global Adaptation Initiative Country Index (ND-GAIN). 2025. University of Notre Dame.

Figure 5: Human Development Index and Climate Awareness



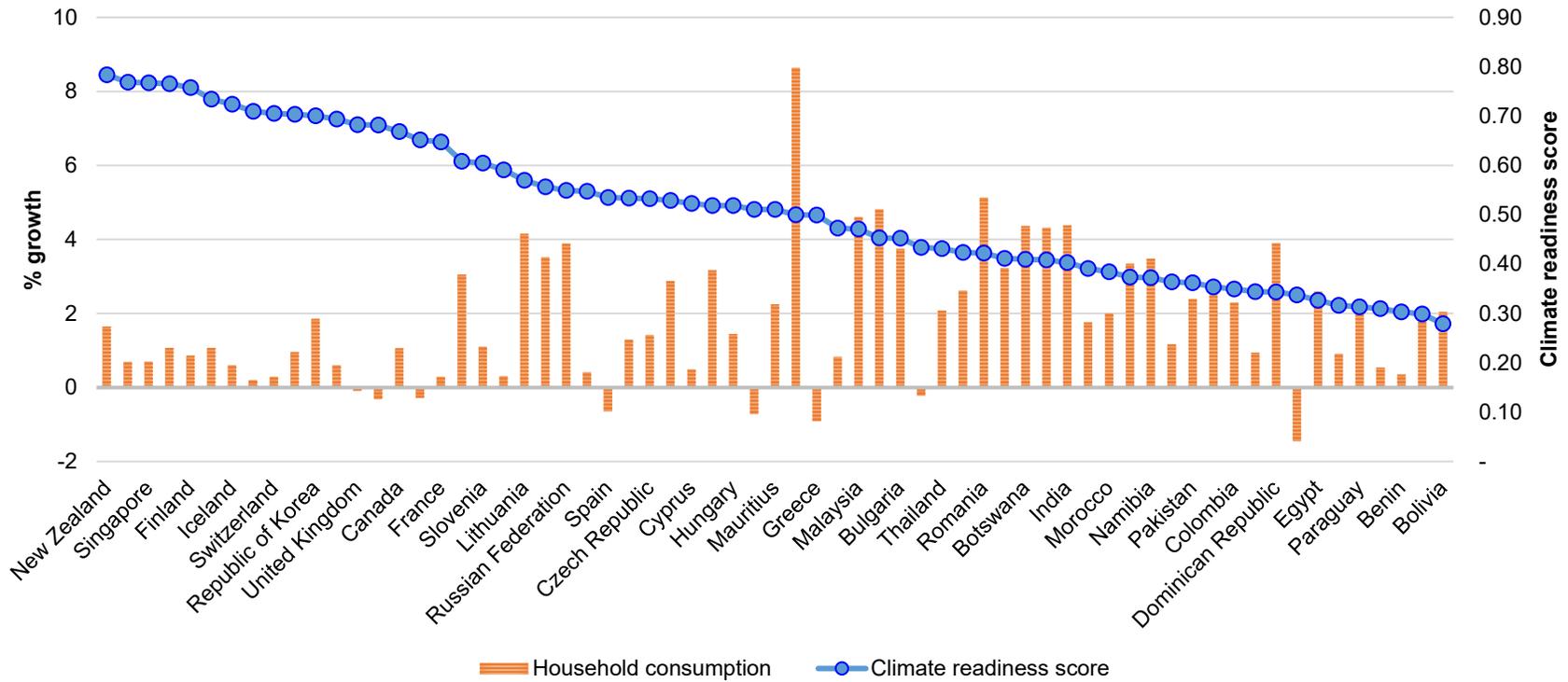
Source: United Nations Development Programme. Human Development Data. <https://hdr.undp.org/data-center> (accessed 30 June 2025); Notre Dame Global Adaptation Initiative Country Index (ND-GAIN). 2025. University of Notre Dame.

Figure 6: Gross Fixed Capital Formation and Climate Awareness



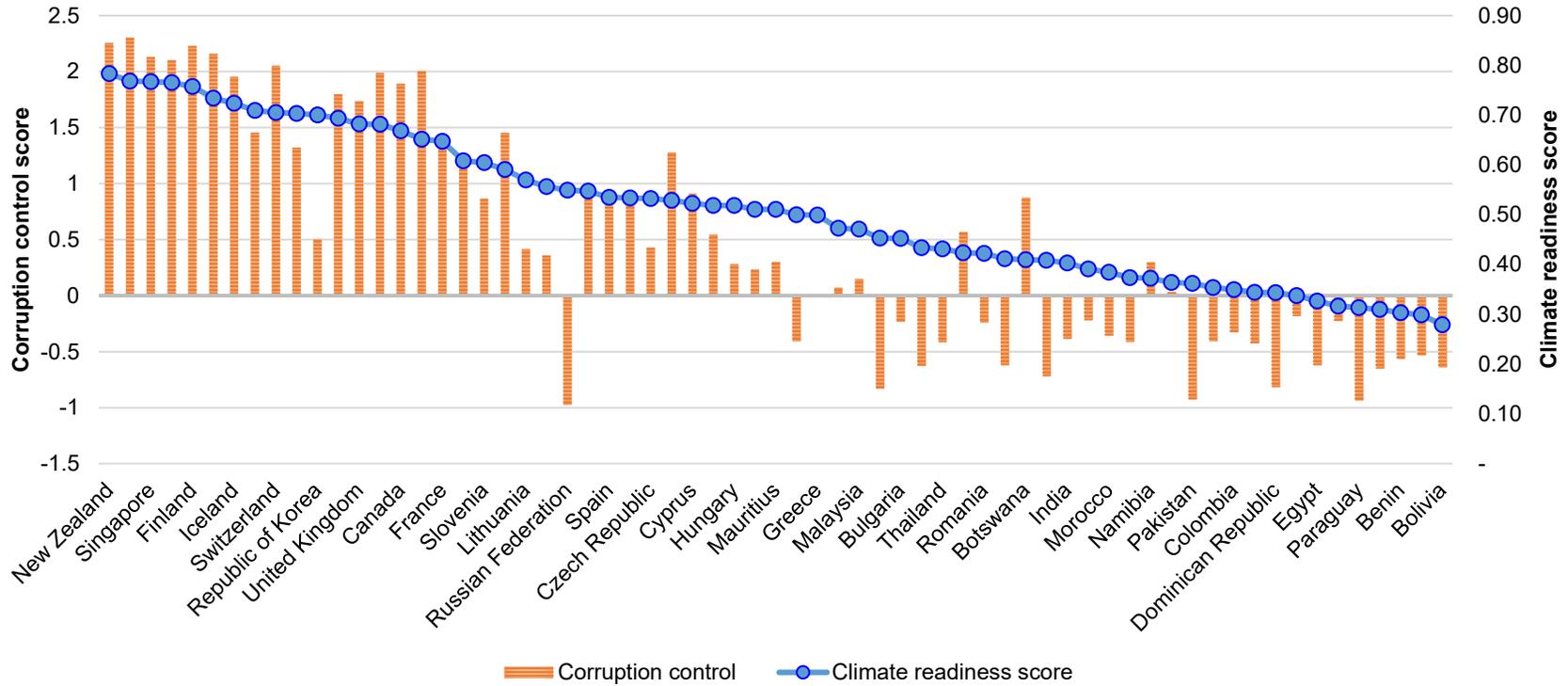
Source: World Bank. World Development Indicators. <https://databank.worldbank.org/source/world-development-indicators> (accessed 30 June 2025); Notre Dame Global Adaptation Initiative Country Index (ND-GAIN). 2025. University of Notre Dame.

Figure 7: Household Private Consumption and Climate Awareness



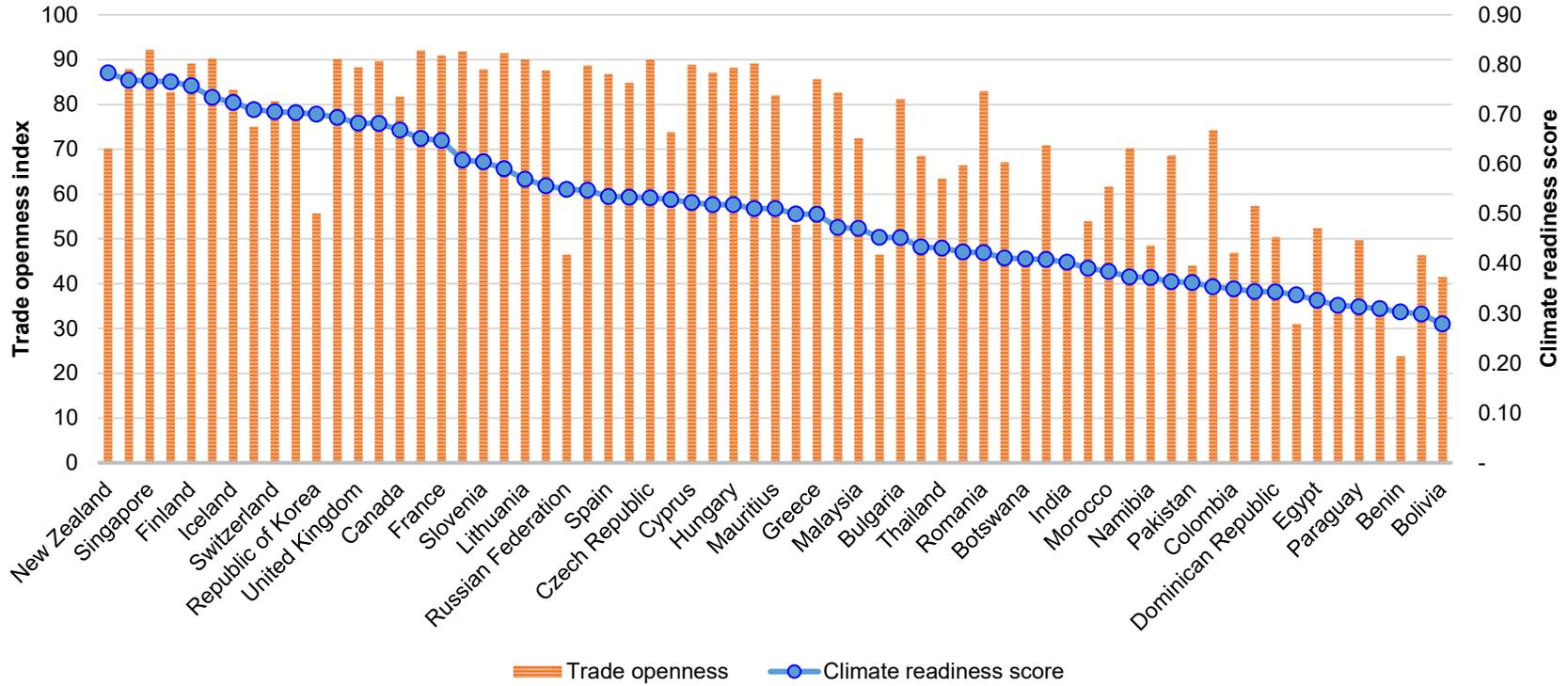
Source: World Bank. World Development Indicators. <https://databank.worldbank.org/source/world-development-indicators> (accessed 30 June 2025); Notre Dame Global Adaptation Initiative Country Index (ND-GAIN). 2025. University of Notre Dame.

Figure 8: Corruption Control and Climate Awareness



Source: World Bank. Worldwide Governance Indicators, 2024 Update. <http://www.govindicators.org/> (accessed 30 June 2025); Notre Dame Global Adaptation Initiative Country Index (ND-GAIN). 2025. University of Notre Dame.

Figure 9: Trade Openness (Globalization) and Climate Awareness



Source: ETH Zürich. KOF Globalisation Index. <https://kof.ethz.ch/en/data.html> (accessed 30 June 2025); Notre Dame Global Adaptation Initiative Country Index (ND-GAIN). 2025. University of Notre Dame.

## **4. DATA AND METHODOLOGY**

### **4.1. Data and Descriptive Statistics**

This study aims to investigate the influence of digitalization on climate awareness, utilizing the ND-GAIN countries' overall readiness score against climate change as a proxy for climate change awareness. The CRS measures a country's preparedness to leverage investments for adaptive actions and enhance resilience to climate change (ND-GAIN, 2023). Climate readiness and climate awareness, while distinct terms, share overlapping components and, hence, are strongly intertwined. There are strong empirical grounds to argue that climate readiness can serve as an effective proxy for climate awareness, as demonstrated by recent empirical studies. For instance, studies suggest that heightened awareness of climate risks drives greater adaptive capacity and preparedness (Marshall et al., 2013; Arıkan and Günay, 2021; Epule et al., 2021). Similarly, Yao et al. (2024) emphasize the role of societal awareness in enhancing national readiness and response to climate change. Therefore, we utilize CRS as a measure of climate awareness in our study. Furthermore, there is no country-wise climate awareness index with comprehensive data.

To represent digitalization, we have found five indicators potentially indicative of a country's level of digitalization: individuals using the internet (% of the population), fixed broadband subscriptions (per 100 people), mobile cellular subscriptions (per 100 people), ICT goods imports (percentage of total goods imports), and ICT goods exports (percentage of total goods export). These variables are interconnected and vary in scale. Due to the presence of several control variables and a limited data period of 16 years, employing all these variables may generate complexity in model selection and estimation, potentially leading to spurious results. Thus, to address these issues and reduce data dimensionality, we utilize principal component analysis to construct an index; we name the index as the country digitalization index (CDI), based on the aforementioned five digitalization-related variables (Table 1). Though this technique reduces the dimensionality of the data, it preserves as much variance as possible (Cui et al., 2021). CDI is used as a proxy for digitalization.

In addition, we incorporate six vital control variables, including the share of renewable energy consumption to total energy consumption (as a proxy for green development), HDI (as a proxy for sustainable economic development), gross fixed capital formation, per capita household consumption growth, control of corruption, and trade globalization (Table 1). The dataset comprises annual panel data from 65 countries spanning 16 years from 2005 to 2020, resulting

in 1,040 country–year observations.<sup>1</sup> The data availability restricts the sample period and size.

Table 1 illustrates the definition, description, and data sources of variables.

**Table 1. Definitions of All Variables and Data Sources**

Variables	Variable Types	Variable Definitions	Sources
CRS	Dependent	Countries' overall readiness score against climate vulnerability, considering economic, social, and governance readiness.	University of Notre Dame ( <a href="https://gain.nd.edu/our-work/country-index/rankings/">https://gain.nd.edu/our-work/country-index/rankings/</a> )
INT	Explanatory	Individuals using the internet (% of the population).	International Telecommunication Union (ITU) World Telecommunication/ICT indicators database
BB	Explanatory	Fixed broadband subscriptions (per 100 people).	ITU World Telecommunication/ICT indicators database
MOB	Explanatory	Mobile cellular subscriptions (per 100 people).	ITU World Telecommunication/ICT indicators database
ICT_IMP	Explanatory	Information and communications technology (ICT) goods imports (% of total goods imports).	UN Trade and Development (UNCTAD)
ICT_EXP	Explanatory	ICT goods exports (% of total goods export).	UNCTAD
CDI	Explanatory	The country digitalization index represents the country's digitalization position.	The CDI is constructed using 5 variables: INT, BB, MOB, ICT_IMP, and ICT_EXP through employing the principal component analysis (PCA) <sup>2</sup> technique. STATA software is used for the analysis.
RE	Control	Renewable energy consumption (% of total final energy consumption).	International Energy Agency, International Renewable Energy Agency, United Nations Statistics Division, World Bank, World Health Organization. 2023. Tracking Sustainable Development Goal 7: The Energy Progress Report
HDI	Control	The Human Development Index is a summary measure of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and having a decent standard of living.	United Nations Development Programme ( <a href="https://hdr.undp.org/data-center/documentation-and-downloads">https://hdr.undp.org/data-center/documentation-and-downloads</a> )
GFCF	Control	Gross fixed capital formation (% of gross domestic product): land improvement, physical capital, construction.	World Bank national accounts data

*Continued on the next page*

<sup>1</sup> Our sample includes 65 countries: Belgium, Belize, Benin, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Canada, Chile, the People's Republic of China, Colombia, Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, India, Indonesia, Israel, Italy, Japan, Kazakhstan, the Republic of Korea, Latvia, Lithuania, Luxembourg, Malaysia, Mauritius, Mexico, Moldova, Morocco, Namibia, the Netherlands, New Zealand, Norway, Pakistan, Paraguay, Peru, Poland, Portugal, Romania, the Russian Federation, Senegal, Singapore, Slovenia, South Africa, Spain, Sweden, Switzerland, Tanzania, Thailand, the United Kingdom, and the United States.

<sup>2</sup> PCA is a prevalent multivariate statistical method utilized to decrease the dimensionality of large datasets, thereby enhancing interpretability without significant information loss (Cui et al., 2021). It accomplishes this by transforming the original variables into a fresh set of orthogonal variables, termed principal components, which represent linear combinations of the original variables.

Variables	Variable Types	Variable Definitions	Sources
HC	Control	Households and non-profit institutions serving households (NPISHs)' final consumption expenditure per capita growth (annual %)	World Bank national accounts data
CORR	Control	Control of corruption: perception of public power being exercised for private gain. A higher score means more control over corruption, while a lower score means less control over corruption.	World Bank worldwide governance indicators
TO	Control	Trade globalization: trade regulations, taxes, tariffs, and agreements.	KOF Globalization Index

Source: Authors.

Table 2 presents the summary statistics for all variables under investigation. Skewness values reveal a mixed distribution of tails, with four variables exhibiting negative skewness (left-sided) and the remaining four showing positive skewness (right-sided). High kurtosis values across most variables suggest heavy tailed distributions and the presence of potential outliers. These observations collectively indicate non-normality in the sampled data series, a conclusion further supported by significant Jarque–Bera statistics.

**Table 2. Results of Summary Statistics**

Statistics	CRS	CDI	RE	HDI	GFCF	HC	CORR	TO
Mean	0.511	0.000	23.352	0.796	22.712	1.851	0.469	70.693
Maximum	0.823	3.189	90.930	0.963	44.519	19.524	2.459	94.875
Minimum	0.267	(2.703)	0.470	0.421	10.687	(16.469)	(1.356)	19.974
Std. Dev.	0.149	0.969	18.071	0.124	5.256	4.133	1.021	19.403
Skewness	0.262	(0.097)	1.296	(0.860)	1.024	(0.410)	0.381	(0.649)
Kurtosis	1.920	2.570	4.880	3.073	5.310	5.757	1.855	2.167
Jarque–Bera	62.38***	9.63***	444.35***	128.51***	412.87***	358.65***	81.97***	103.05***

( ) = negative.

Notes: CRS, CDI, RE, HDI, GFCF, HC, CORR, and TO represent countries' overall readiness score, country digitalization index, renewable energy, Human Development Index, gross fixed capital formation, per capita household consumption growth, corruption, and trade globalization, respectively. Std. Dev. indicates standard deviation. '\*\*\*', '\*\*', and '\*' indicate the significance levels at 1%, 5%, and 10%, respectively.

Source: Authors' calculations.

The correlation matrix, as exhibited in Table 3, discloses that climate awareness exhibits a positive correlation with most of the studied variables, except for renewable energy and household consumption. Among other variable pairs, the correlations vary, showing a mix of positive and negative associations.

**Table 3. Correlation Matrix**

Variables	CRS	CDI	RE	HDI	GFCF	HC	CORR	TO
CRS	1							
CDI	0.038	1						
RE	(0.171)***	0.022	1					
HDI	0.839***	0.095***	(0.343)***	1				
GFCF	0.031	(0.061)**	0.017***	(0.100)***	1			
HC	(0.149)***	(0.211)***	(0.019)	(0.179)***	0.301***	1		
CORR	0.871***	(0.014)	(0.057)*	0.738***	(0.043)	(0.177)***	1	
TO	0.689***	0.063**	(0.266)***	0.794***	(0.090)***	(0.143)***	0.650***	1

( ) = negative.

CDI = country digitalization index, CORR = corruption, CRS = climate readiness score, GFCF = gross fixed capital formation, HC = household consumption, HDI = Human Development Index, RE = renewable energy, TO = trade openness.

Note: '\*\*\*' and '\*' indicate the significance levels at 1% and 5%, respectively.

Source: Authors' calculations.

## 4.2. Methodology

Our study investigates the relationship between digitalization and climate awareness, along with other critical control variables, using the following basic model specification:

$$CRS_{it} = \alpha + \beta_1 CDI_{it} + \beta_2 RE_{it} + \beta_3 HDI_{it} + \beta_4 GFCF_{it} + \beta_5 HC_{it} + \beta_6 CORR_{it} + \beta_7 TO_{it} + \epsilon_{it}, \quad (1)$$

where, *CRS*, *CDI*, *RE*, *HDI*, *GFCF*, *HC*, *CORR*, and *TO* represent the readiness score against climate vulnerability, the country digitalization index, the share of renewable energy consumption to total energy consumption, the Human Development Index, gross fixed capital formation, households' and non-profit institutions serving households' (NPISHs') final consumption, control of corruption, and trade globalization, respectively.  $\alpha$  denotes the intercept,  $\epsilon$  represents the error term,  $\beta$  represents the parameters and can be interpreted as elasticities of the dependent variable relative to each explanatory variable. *i* denotes the cross-sectional unit (i.e., the country), and *t* is time.

Before proceeding with the econometric analyses, it is necessary to conduct pre-estimation checks, particularly regarding stationarity, slope heterogeneity, and cross-sectional dependence (CSD) issues. Following the identification of these issues, i.e., stationarity, slope heterogeneity, and CSD (Subsection 5.1), we, as suggested by former studies (e.g., Zoundi,

2017; Rahman et al., 2021; Uddin et al., 2025), employ Kao's (1999) test for checking the presence of long run cointegration between the variables. This test addresses both stationarity and CSD issues in the dataset and is suitable for datasets with a relatively large number of variables (eight) and small sample sizes, particularly when time ( $T=16$ ) is less than cross-section units ( $N=65$ ), such as ours (Kao, 1999; Gutierrez, 2003; Gengenbach et al., 2005). Additionally, we employ Pedroni's (1999) and Westerlund's (2007) cointegration tests for robustness, given the several data issues (following the literature, including Zoundi, 2017; Galán-Gutiérrez et al., 2023).

Given the inherent dataset challenges mentioned above and the estimation of cointegration (Subsection 5.2), feasible generalized least squares, proposed by Parks (1967), and panel-corrected standard errors by Beck and Katz (1995) are employed to estimate the long-term relationship between variables as specified in equation (1). The PCSE model generates precise standard error estimates while minimizing efficiency loss, particularly under large cross-sectional units (i.e.,  $N>T$ ) (Reed and Webb, 2010; Millo, 2017). In addition, both FGLS and PCSE models can tackle CSD, heteroscedasticity, and serial correlation issues within panels, providing robust long-term estimates (Wang and Ibrahim, 2024; Uddin et al., 2025).

Though the FGLS and PCSE models are effective in tackling various issues within panel datasets, the existence of endogeneity issues in explanatory variables may undermine the accuracy and consistency of their estimates. Endogeneity concerns often arise because of several reasons, such as omitted variables, measurement error, or simultaneous causality, all of which can lead to unfair and inconsistent results in static or dynamically underspecified models (Roodman, 2009; Hasan et al., 2023; Mugume and Bulime, 2024). Furthermore, panel data models may suffer from poor instruments or overidentification concerns, which further affect the trustworthiness of the estimates when using conventional models (Hasan et al., 2023; Uddin et al., 2025). To mitigate this concern and validate the baseline outcomes (PCSE and FGLS), employing a panel dynamic instrument-based technique, such as system generalized method of moments, two stage least squares, or dynamic common correlated effects, is indispensable. Given our data features, notably CSD and  $N>T$ , where endogeneity is likely owing to feedback effects (lagged dependent variable) and omitted variable bias, the two-step system GMM approach established by Arellano and Bover (1995) and Blundell and Bond (1998) is particularly well suited (Lau et al., 2018). Furthermore, system GMM outperforms other dynamic models, such as 2SLS. While other models rely on accurately identifying external instruments to manage endogeneity, which is very hard to attain, system GMM leverages internal instruments in a

theoretically solid manner to handle endogeneity effectively and generate more credible and robust results.

In addressing non-normality in data series and potential tailed dependence, we also utilize panel quantile regression developed by Koenker (2004). This approach offers a comprehensive understanding of the dependent variable by specifying the complete conditional distribution, thus enabling us to address distributional heterogeneity within panel data effectively (Muhammad et al., 2020). Unlike conventional models such as fixed effects or random effects, panel QR is better suited for capturing distributional heterogeneity (Galvao, 2011; Akram et al., 2020). To enhance the robustness of our analysis, we specifically employ bootstrapped panel quantile regression, which is known for its resilience to distributional assumptions and its suitability for small sample sizes ( $T < N$ ) (Nikitina et al., 2019; Guo et al., 2023). Furthermore, this method offers more accurate standard errors and confidence intervals, thereby enhancing the reliability of the estimates, especially in the presence of heteroscedasticity or serial correlation (Guo et al., 2023).

## **5. RESULT ANALYSIS AND DISCUSSION**

### **5.1. Cross-sectional Dependence, Slope Heterogeneity, and Panel Unit Root Test Analysis**

Prior to selecting and estimating regression models, it is imperative to address several econometric issues commonly encountered in panel data, including CSD, stationarity, and cointegration. CSD, a prevalent phenomenon in panel datasets, arises when observations across different cross-sectional units, such as countries, exhibit correlations due to spatial spillovers, common shocks, network effects, or unobserved heterogeneity (Maza and Gutiérrez-Portilla, 2022; Naz, 2023). Failing to appropriately account for CSD in the analysis may lead to inconsistent outcomes (Abban and Hasan, 2021; Maza and Gutiérrez-Portilla, 2022). Traditional techniques, particularly first generation methods, often struggle to identify CSD. Therefore, we employ second generation techniques, such as the Breusch and Pagan (1980) Lagrange multiplier (LM) test and the Pesaran (2004) cross-sectional dependence test. Given the limited observations, these techniques are suitable for our analysis, where the number of time periods ( $T$ ) is less than the number of cross-sectional units ( $N$ ). The outcomes, exhibited in Table 4, indicate that both tests reject the null hypothesis of no CSD at 1% significance. Thus, the empirical findings confirm the presence of CSD across all data series.

**Table 4. Cross-sectional Dependence Estimates**

<b>Test</b>	<b>CRS</b>	<b>CDI</b>	<b>RE</b>	<b>HDI</b>	<b>GFCF</b>	<b>HC</b>	<b>CORR</b>	<b>TO</b>
CD-tests	48.50***	65.37***	16.03***	170.97***	20.42***	93.00***	0.56	29.75***
p-value	0.000	0.023	0.000	0.000	0.000	0.000	0.57	0.000
Breusch–Pagan LM	11443.94***	21399.4***	15408.51***	29439.17***	7489.23***	11333.13***	7622.45***	9269.59***
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

CD = cross-sectional dependence, CDI = country digitalization index, CORR = control of corruption, CRS = climate readiness score, GFCF = gross fixed capital formation, HC = household consumption, HDI = Human Development Index, LM = Lagrange multiplier, RE = renewable energy, TO = trade openness.

Note: \*\*\* indicates a significance level of 1%.

Source: Authors' calculations.

Table 5 displays the outcomes of the slope homogeneity test (proposed by Pesaran and Yamagata, 2008). The findings reveal that both delta and adjusted delta statistics reject the null hypothesis of slope homogeneity at the 1% level, indicating the presence of slope heterogeneity in our model. Given the existence of CSD and slope heterogeneity in our model, we have carefully selected our econometric techniques, suggested by the literature, to address these issues to yield reliable outcomes.

**Table 5. Slope Homogeneity Test (Pesaran and Yamagata, 2008) Estimates**

<b>Test Statistics</b>	<b>Value</b>
Delta	8.890*** (0.000)
Adjusted delta	13.440*** (0.000)

Note: '\*\*\*' indicates the significance level at 1%.

Source: Authors' calculations.

Given the existence of CSD in all data series, we utilize second generation panel unit root tests: the cross-sectional augmented Im, Pesaran, and Shin (CIPS) test and the cross-sectional augmented Dickey–Fuller (CADF) test, as proposed by Pesaran (2007). These tests are also useful for datasets exhibiting non-normality and small sample sizes. Unlike traditional ADF techniques, which do not account for CSD issues and may, therefore, fail to detect unit roots in the data, both CIPS and CADF tests account for CSD and offer reliable outcomes (Naz, 2023; Li et al., 2024). The outcomes documented in Table 6 illustrate the results of the CADF and CIPS tests. Both tests suggest that most variables exhibit nonstationarity at their levels. However, they all become stationary at the first difference level with the 1% to 5% significance levels, indicating that all variables are integrated in order 1.

**Table 6. Second-generation Unit Root Tests**

<b>Variables</b>	<b>CIPS</b>		<b>CADF</b>	
	<b>Level</b>	<b>First difference</b>	<b>L=Level</b>	<b>First difference</b>
<i>CRS</i>	(2.394)***	(3.609)***	(1.977)**	(3.283)***
<i>CDI</i>	(1.961)	(2.830)***	(1.815)	(2.044)**
<i>RE</i>	(1.550)	(3.458)***	(1.405)	(2.151)***
<i>HDI</i>	(1.777)	(3.182)***	(1.965)**	(3.358)***
<i>GFCF</i>	(1.542)	(3.020)***	(1.491)	(1.995)**

*Continued on the next page*

Variables	CIPS		CADF	
	Level	First difference	L=Level	First difference
HC	(2.167)**	(3.816)***	(1.552)	(2.212)***
CORR	(1.882)	(3.412)***	(1.688)	(2.510)***
TO	(2.767)***	(3.739)***	(2.525)***	(2.470)***

( ) = negative.

CADF = cross-sectional augmented Dickie–Fuller test, CDI = country digitalization index, CIPS = cross-sectional augmented Im, Pesaran, and Shin test, CORR = control of corruption, CRS = climate readiness score, GFCF = gross fixed capital formation, HC = household consumption, HDI = Human Development Index, RE = renewable energy, TO = trade openness.

Note: '\*\*\*' and '\*\*' denote the significance levels of 1% and 5%, respectively.

Source: Authors' calculations.

## 5.2. Panel Cointegration Test

Given that all variables under investigation are stationary at the first difference, it is imperative to assess for cointegration among the variables to evade potential spurious regression glitches. In the case of CSD and stationarity issues in the panel dataset, the literature suggests several panel cointegration tests, including Pedroni's (1999), Kao's (1999), and Westerlund's (2007) tests (Zoundi, 2017; Galán-Gutiérrez et al., 2023; Uddin et al., 2025). Hence, we employ all three tests to provide robust outcomes. Table 7 reports the estimates of the cointegration test. Most test statistics in Kao's test and all test statistics in Pedroni's and Westerlund's tests reject the null hypothesis of no cointegration at the 1% to 10% significance levels, suggesting the presence of a long-term association among the variables.

**Table 7. Panel Cointegration Tests**

Cointegration Test	Statistics	Prob.
<b><i>Kao's Residual Cointegration Test</i></b>		
Modified Dickey–Fuller t	(0.5906)	0.2774
Dickey–Fuller t	(1.3714)*	0.0851
Augmented Dickey–Fuller t	(1.4287)*	0.0766
Unadjusted modified Dickey–Fuller t	(1.0113)	0.1559
Unadjusted Dickey–Fuller t	(1.6503)**	0.0494
<b><i>Pedroni Cointegration Test</i></b>		
Modified Phillips–Perron t	11.4886***	0.0000
Phillips–Perron t	(6.6349)***	0.0000
Augmented Dickey–Fuller t	(6.3877)***	0.0000
<b><i>Westerlund Cointegration Test</i></b>		
Variance ratio	2.5946***	0.0047

( ) = negative.

Notes: '\*\*\*', '\*\*', and '\*' indicate the significance levels at 1%, 5%, and 10%, respectively. Null hypothesis = no cointegration.

Source: Authors' calculations.

### 5.3. Results of Panel-corrected Standard Errors and Feasible Generalized Least Squares Estimates

Having confirmed the cointegration among variables, we proceed to estimate their long run association using the PCSE approach (Beck and Katz, 1995). Given our panel structure ( $T < N$ ) and the presence of CSD, PCSE is well fitted. It is also recommended in recent literature (e.g., Arora and Kashiramka, 2023; Wang and Ibrahim, 2024; Uddin et al., 2025), as it accounts for various data issues encountered in panel data analysis, including CSD, serial correlation, heteroscedasticity, and small sample sizes. Additionally, we utilize the feasible generalized least squares technique for robustness purposes.

Table 8 presents both PCSE and FGLS estimates. Both models show that the lagged term of the dependent variable (lagged CRS) is positive and highly significant (0.933) at the 1% level of significance, reflecting very robust persistence in climate awareness across time. That is, a one-unit rise in CRS in the preceding year leads to an increase of about 0.93 units in CRS in the present year. The coefficient of the main explanatory variable—digitalization (CDI)—is negative and marginally significant (at the 10% significance level), while its squared term is positive and highly significant (at the 1% significance level). This pattern indicates that digitalization has a nonlinear and U-shaped association with climate awareness. That is, the benefits of digitalization for environmental awareness materialize once a certain digital maturity threshold is achieved, likely tied to digital maturity, policy integration, or the scale of user engagement. Likewise, the share of renewable energy consumption exhibits a nonlinear U-shaped correlation with climate awareness, as the linear term of RE is negative and significant, while its squared term is positive but marginally significant ( $p < 0.10$  for FGLS but not significant for PCSE). This implies that the share of RE negatively affects climate awareness at the initial stage; however, as the renewable energy adoption matures, it starts to favorably influence climate awareness among the public.

Among the control variables, HDI positively and significantly influences climate awareness, according to FGLS estimates, while PCSE estimates indicate a positive but insignificant effect. Accordingly, the share of GFCF to the gross domestic product (GDP) exerts a positive and moderately significant effect on climate awareness across both models. Furthermore, control of corruption and household consumption patterns also significantly and favorably contribute to public climate consciousness. Conversely, trade openness has no significant effect. Overall, our findings demonstrate strong robustness, as both PCSE and FGLS models yield almost analogous outcomes across key variables in our analysis.

**Table 8. Panel-corrected Standard Errors and Feasible Generalized Least Squares Estimates**

<b>Dependent Variable: CRS</b>		
<b>Variables</b>	<b>PCSE</b>	<b>FGLS</b>
<i>L.CRS</i>	0.9330*** (0.043)	0.9330*** (0.011)
<i>CDI</i>	-0.0013* (0.001)	-0.0014* (0.001)
<i>CDI</i> <sup>2</sup>	0.0035*** (0.001)	0.0035*** (0.001)
<i>RE</i>	-0.0002** (0.001)	-0.0002** (0.001)
<i>RE</i> <sup>2</sup>	0.0000 (0.000)	0.0000* (0.000)
<i>HDI</i>	0.0303 (0.027)	0.0303** (0.012)
<i>GFCF</i>	0.0003* (0.000)	0.0003** (0.000)
<i>HC</i>	0.0004** (0.000)	0.0004** (0.000)
<i>CORR</i>	0.0067* (0.004)	0.0067*** (0.001)
<i>TO</i>	0.0000 (0.000)	0.0000 (0.000)
Constant	0.0011 (0.006)	0.0011 (0.008)
Observations	975	975
R-squared	0.9834	-
<i>Wald statistics</i>		
Chi2	13001.94	57805.40
(P-value)	0.00	0.00

CDI = country digitalization index, CORR = control of corruption, CRS = climate readiness score, FGLS = feasible generalized least squares, GFCF = gross fixed capital formation, HC = household consumption, HDI = Human Development Index, L.CRS = lagged climate readiness score, PCSE = panel corrected standard errors, RE = renewable energy, TO = trade openness.

Notes: The table reports the results of panel-corrected standard errors (PCSE) and feasible generalized least squares (FGLS) estimates. The values in the parentheses are standard errors. '\*\*\*', '\*\*', and '\*' indicate the significance levels at 1%, 5%, and 10%, respectively.

Source: Authors' calculations.

#### **5.4. Results of System Generalized Method of Moments Estimation**

To handle potential endogeneity of our dataset and further verify the robustness of our baseline (PCSE and FGLS) findings, we implement a two-step system GMM method. This approach is particularly well suited in our dynamic panel dataset where the dependent variable (CRS) is expected to persist over time, and certain explanatory factors are likely to be endogenous. Following Roodman (2009), we meticulously minimize instrument proliferation by collapsing instruments and restricting lags to uphold parsimony. Our specification embraces 17

instruments—well below the number of cross-sectional units (N = 65)—thereby satisfying the conventional rule of thumb and averting likely overfitting.

Table 9 exhibits the GMM outcomes. The diagnostic examinations substantiate the model's reliability and validity. The Arellano–Bond test for AR(1) is highly significant ( $p < 0.01$ ), which is expected for first-differenced residuals in a correctly specified dynamic panel model. Importantly, AR(2) is insignificant ( $p = 0.249$ ), implying no second order autocorrelation, a critical condition for the GMM model's consistency. The Sargan ( $p = 0.994$ ) and Hansen ( $p = 0.934$ ) tests suggest that the instruments used in this model are justifiable and not overfitting the model. Furthermore, the difference-in-Hansen tests indicate that the instrument subsets are properly exogenous, which enhances confidence in the model's identification technique, thereby supporting the choice of system GMM over differenced GMM.

The GMM estimations largely corroborate our baseline findings, especially concerning dynamic and nonlinear relationships. The lagged dependent variable (L.CRS) is positive and highly significant at the 1% significance level, further corroborating the strong persistence of climate awareness across time. Both CDI and RE continue to show nonlinear U-shaped associations with climate awareness; notably, the squared terms of CDI and RE are positive and significant, although the linear term of CDI is insignificant but is negative. Control factors, such as control of corruption and household consumption, uphold their strong and beneficial influences on climate awareness. Other controls (HDI, GFCF, and TO) are statistically insignificant in the GMM framework, although their coefficients are broadly consistent (positive) with expectations and baseline model estimates. This suggests that their effects are less robust when stricter endogeneity controls are applied under GMM estimates. In summary, our GMM estimates align closely with the findings of our baseline models, while highlighting the significant nonlinear relationships of digitalization and renewable energy with climate awareness.

**Table 9. Two-step System Generalized Method of Moments Estimation**

<b>Dependent Variable: CRS</b>		
<b>Variable</b>	<b>Coefficient</b>	<b>Standard errors</b>
<i>L.CRS</i>	0.8804***	0.0354
<i>CDI</i>	-0.0003	0.0014
<i>CDI</i> <sup>2</sup>	0.0029***	0.0008
<i>RE</i>	-0.0004**	0.0002
<i>RE</i> <sup>2</sup>	0.0000*	0.0000

*Continued on the next page*

<b>Dependent Variable: CRS</b>		
<b>Variable</b>	<b>Coefficient</b>	<b>Standard errors</b>
<i>HDI</i>	0.0150	0.0783
<i>GFCF</i>	0.0003	0.0002
<i>HC</i>	0.0003*	0.0002
<i>CORR</i>	0.0125**	0.0052
<i>TO</i>	0.0002	0.0002
<i>Constant</i>	0.0293	0.0442
<i>AR(1)</i>	-3.48 (P = 0.001 )	
<i>AR(2)</i>	1.15 (P = 0.249)	
Sargam test- $\chi^2(6)$	0.73 (P = 0.994)	
Hansen test- $\chi^2(6)$	1.84 (P = 0.934)	
Difference-in-Hansen Test	1.32 (p = 0.725)	
No. of instruments	17	
No. of observations	975	
No. of countries	65	

CDI = country digitalization index, CORR = control of corruption, CRS = climate readiness score, GFCF = gross fixed capital formation, HC = household consumption, HDI = Human Development Index, L.CRS = lagged climate readiness score, RE = renewable energy, TO = trade openness.

Notes: The table reports the results of the two-step system GMM approach, estimated with robust standard errors adjusted for finite sample bias (small) using the collapse form, following Roodman (2009). L.CRS,  $CDI^2$ , and  $RE^2$  are lagged values of CRS, CDI squared, and RE squared, respectively. ‘\*\*\*,’ ‘\*\*,’ and ‘\*’ specify the significance levels at 1%, 5%, and 10%, respectively.

Source: Authors’ calculations.

## 5.5. Results of Panel Quantile Estimation

Given that our dataset exhibits non-normality and potential tail dependence, we employ bootstrapped panel quantile regression to examine how digitalization influences climate awareness across different levels of awareness. This methodology is particularly relevant due to its robustness to distributional assumptions, making it well suited for small sample sizes and heterogeneous panel data (Nikitina et al., 2019; Guo et al., 2023).

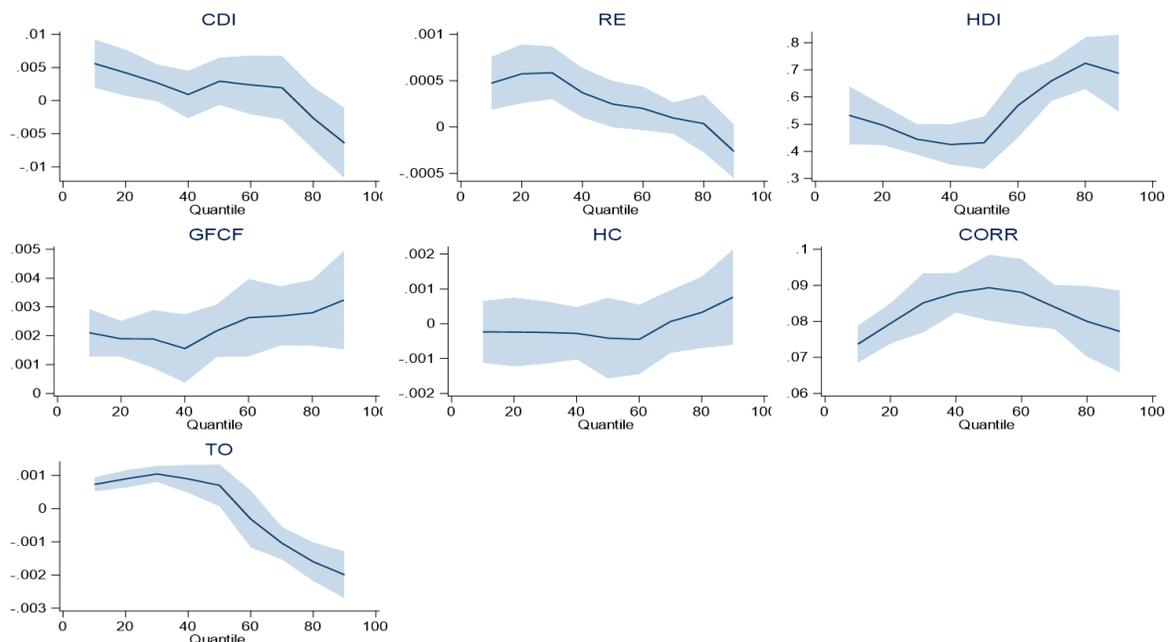
The outcomes of the quantile regression analysis are displayed in Figure 10. The findings indicate that digitalization positively affects climate awareness, with statistical significance primarily observed at the lower quantiles (0.10–0.20). This suggests that digitalization plays a critical role in raising awareness in countries where climate consciousness is relatively low. However, at higher quantiles (0.80–0.90), the effect turns negative and insignificant, indicating that digitalization’s influence diminishes in more environmentally aware nations.

Similarly, renewable energy consumption has a positive and significant effect across most quantiles, except at 0.70 and 0.80. Indicators such as HDI, GFCF, and corruption control consistently exhibit strong positive correlations with climate awareness across all quantiles, highlighting their importance in shaping climate perceptions.

Interestingly, trade globalization demonstrates a mixed pattern—it is positively associated with climate awareness at lower to middle quantiles (0.10–0.50) but turns significantly negative at higher quantiles (0.70–0.90). This suggests that while trade exposure may enhance awareness in less environmentally conscious countries (via knowledge spillovers and international agreements), in nations with high awareness, trade activities might shift focus away from climate issues. Household consumption shows a negative but statistically insignificant effect across most quantiles (0.10–0.60), indicating that consumption patterns do not strongly influence climate awareness.

Overall, our panel quantile regression findings, focusing on linear effects, are largely consistent with the directional influence of variables observed in our earlier mean-effect model estimates (PCSE, FGLS, and system GMM), with only minor deviations, underscoring the robustness of our results. The observed coefficient variations across quantiles, especially for digitalization and trade globalization, suggest strong quantile dependence, implying that the relationship between these variables and climate awareness varies across different levels of climate awareness.

**Figure 10: Plots of Panel Quantile Regression Coefficients**



*Continued on the next page*

CDI = country digitalization index, CORR = control of corruption, GFCF = gross fixed capital formation, HC = household consumption, HDI = Human Development Index, RE = renewable energy, TO = trade openness.

Notes: The x-axis represents the diverse quantile levels of dependent variables (CRS), and the y-axis denotes the coefficient values of all exogenous variables (CDI, RE, HDI, GFCF, HC, CORR, and TO). The blue line shows the coefficients of panel quantile regression, and the gray area covers the 95% confidence interval.

Source: Authors' calculations.

## 5.6. Discussion of Results

Our analysis, represented above, discloses several vital insights into the dynamics of climate awareness and digitalization. Remarkably, including a lagged term of the dependent variable (L.CRS) in all models results in a consistently positive and very robust coefficient, implying a strong temporal persistence in climate awareness among the population. This implies that countries with great levels of awareness in the past are more likely to maintain or increase that awareness in subsequent periods. This outcome is consistent with the informational habituation and awareness reinforcement hypothesis, where prior environmental engagement fosters sustained public interest and responsiveness to climate action (Kurz et al., 2014; Arıkan and Günay, 2021). It also supports previous empirical research demonstrating that exposure to institutional, media, and educational efforts may result in long-term behavioral and cognitive effects on environmental consciousness (Lee et al., 2015; Ruiu et al., 2022).

The main explanatory variable—digitalization—is found to exert a nonlinear U-shaped association with climate awareness across all estimated models, illustrated by a moderately negative linear coefficient and a very significant positive squared component. This signifies that at the initial stages, digitalization may have a minimal or even negative impact on climate awareness, perhaps owing to infrastructure deficits, digital illiteracy, and fragmented or low quality information prevailing in the countries. However, digitalization begins to significantly improve climate awareness once a certain threshold of digital maturity is crossed, presumably when infrastructure (adequate access), digital literacy, and policy coherence evolve (Charfeddine and Umlai, 2023; Su et al., 2023). Digitalization facilitates easy access to information on climate change and environmental issues through the internet and social media platforms, thus enhancing awareness and understanding of the intricate climate change issues (Hung et al., 2022; Charfeddine and Umlai, 2023). Digital platforms enable the dissemination of climate-related information through targeted communication and awareness campaigns (Balogun et al., 2020). Additionally, digital platforms may foster the formation of virtual communities and networking among individuals interested in environmental sustainability, facilitating knowledge sharing, collaboration, and collective action on climate-related issues (Xu et al., 2022). Theoretically, this

result is consistent with the network externalities hypothesis and technology diffusion framework, which emphasize that digital infrastructure's transformational potential only scales after critical mass adoption is attained (Comin and Hobijn, 2004; Sharma et al., 2016; Khan et al., 2024). Earlier empirical research further corroborates this, demonstrating that digitally advanced societies utilize technologies such as artificial intelligence (AI)-powered information platforms, climate applications, and digital media platforms to foster environmental knowledge and citizen engagement (Xu et al., 2022; Khan et al., 2024). Moreover, our findings are partially supported by Hung et al. (2022), who provide evidence that digitalization promotes environmental innovation performance and awareness of its significance.

Likewise, the share of renewable energy consumption exhibits a U-shaped nonlinear pattern. The linear term is negative, but the squared term is positive and substantial, implying that renewable energy adoption may be hampered at first by transitional issues or a lack of public participation. However, as renewables gain wider use and public attention, they begin to positively reinforce climate consciousness. This trend aligns with the ecological modernization hypothesis (Mol and Sonnenfeld, 2000), which holds that technological changes, when backed by policy, investment, and social discourse, raise environmental awareness. Countries with higher renewable share typically have strong and supportive sustainability policy frameworks—such as feed-in tariffs or tax incentives, incentivizing individuals, enterprises, and communities—and active environmental debates, which may raise collective awareness regarding the benefits of renewable energy (Ren21, 2019; Fransen, 2023; Hoa et al., 2024). As individuals observe renewable energy's positive environmental impact, their awareness regarding climate change and the imperative of mitigating its consequences is likely to escalate. Also, it often attracts public discourse and media attention, attributed to the positive environmental impact of using renewable energy against fossil fuels (Toussaint, 2023). Collectively, these factors contribute to the observed positive association between renewable energy share and climate awareness in the long term, as supported by Lucas et al. (2021).

Concerning control variables, control of corruption demonstrates a consistently positive and robust correlation with climate awareness across all models. From a theoretical perspective, good governance strengthens awareness by promoting confidence in institutions, environmental regulations, and policy communications (Usman et al., 2022). This outcome is aligned with previous studies, such as Tabash et al. (2023) and Usman et al. (2022), underscoring that effectively controlling corruption enhances institutional quality (good governance), which may foster transparency, regulatory enforcement, and effective dissemination of environmental

policies, thereby raising environmental awareness. However, the results contradict those of Sahoo et al. (2023), showing that control of corruption diminishes ecological quality. Similarly, the per capita household consumption growth exhibits a positive and solid effect on climate awareness. This suggests that household consumption patterns may exert a strong influence on individuals' perceptions of climate change issues. These findings align with Ricci and Banterle (2020) and Claudelin et al. (2020), who report a significant impact of household consumption patterns on climate change awareness. They link it with consumer environmentalism, where increasing incomes and consumption allow individuals to access more information, make greener choices, and participate in environmental advocacy.

Interestingly, HDI and GFCF are statistically significant in static models (PCSE and FGLS), while they are statistically insignificant under the system GMM approach, although their coefficients are broadly consistent (positive) across all models, which is projected. This suggests that their effects are less robust when stricter endogeneity controls are applied under GMM estimates. However, our findings are consistent with Omri et al. (2019), who suggest that human development does not significantly contribute to environmental sustainability. From their directional consistency, it also aligns with past studies (Tang et al., 2020; Opoku et al., 2022), emphasizing that nations with elevated HDI scores tend to prioritize sustainable development goals, including environmental protection and climate mitigation efforts. Furthermore, our findings partially support previous research by Ajide and Ibrahim (2021) and Meng et al. (2022), which indicates that GFCF positively influences environmental quality. However, our results somewhat contrast with earlier studies, such as Li et al. (2023), which assert a negative impact of GFCF on environmental quality.

In contrast, trade openness exhibits a positive but negligible effect on climate awareness across all models. Trade globalization can stimulate economic activity and industry growth, potentially increasing environmental impact. While it facilitates the exchange of knowledge and technology and environmental standard convergence in less conscious nations, it may lead to carbon leakage or divert attention in more developed contexts. These dynamics are consistent with the views of Peters and Hertwich (2008) and Copeland et al. (2021), who emphasize both the upsides and downsides of globalization in the climate domain.

These insights provide a solid empirical basis for crafting tiered policy interventions, particularly in advancing digital and energy infrastructure, boosting governance, and strategically adapting climate awareness campaigns to country-specific thresholds. Overall, our findings

demonstrate robustness, as all models yield almost analogous outcomes with respect to key variables in our analysis.

## 6. CONCLUSION, POLICY IMPLICATIONS, AND LIMITATIONS

Climate change has emerged as one of our most pressing global challenges, posing significant risks to ecosystems, human health, and economic stability. In response, there is an escalating imperative for individuals and societies to be aware of climate change and its repercussions, enabling them to undertake appropriate actions. The rapid proliferation of digital technologies—spanning the internet, social media, and mobile applications—has transformed the way people access and process information. This raises an important research question: *can digitalization enhance climate awareness?* Despite the relevance of this issue, little empirical research has been conducted on the link between digitalization and climate awareness.

Our study fills this gap by providing new insights into this relationship using a panel dataset covering 65 countries from 2005 to 2020. Employing robust econometric techniques—including panel cointegration tests, panel-corrected standard errors, feasible generalized least squares, two-step system generalized method of moments, and panel quantile regression—we uncover strong evidence supporting the nonlinear U-shaped role of digitalization in raising climate awareness across all models. That is, digitalization initially may have little or an adverse effect on awareness owing to restricted availability or fragmented information, but it becomes substantially favorable when a threshold digital maturity is achieved. The share of renewable energy consumption also exerts a nonlinear (U-shaped) relationship with climate awareness. Controls such as household consumption and corruption control consistently boost climate awareness, highlighting the vital role of empowered, informed people and transparent institutions. Human development, gross fixed capital, and trade openness exhibit expected positive coefficients, but their significance depends on estimation approaches, especially when endogeneity is managed in the GMM approach.

Our findings hold significant implications for policymakers, particularly in the areas of developing digital and renewable energy infrastructure, improving governance, and tailoring climate awareness initiatives to country-specific thresholds. The U-shaped relationship for digitalization suggests that it is essential for policymakers to prioritize not just the expansion of digital access but also the enhancement of digital literacy and the provision of high quality, reliable climate-related information across all segments of society. This approach is crucial to surpass the initial threshold where digitalization effectively boosts awareness. Specifically, governments

should invest in digital education programs, especially in areas where technological access remains constrained. Enhancing digital infrastructure, including the expansion of internet connectivity and the promotion of mobile technology adoption, will significantly bolster the dissemination of climate-related information. Moreover, considering the significant influence of social media on shaping perceptions and behaviors, policymakers may utilize these platforms to share accurate information and enhance awareness. Furthermore, incorporating climate change education into curricula across various disciplines provides future generations with crucial skills for managing environmental challenges.

In a similar vein, policies must facilitate broader adoption and public engagement in renewable energy to fully realize its potential in promoting climate awareness. Governments may pursue public awareness campaigns highlighting renewable energy's potential benefits for both the environment and the economy. The persistently positive influence of corruption control underscores the significance of effective governance, transparency, and regulatory enforcement in fostering climate awareness. The beneficial impact of increasing household consumption suggests that equipping consumers with knowledge and promoting sustainable consumption habits can yield positive results. Although HDI and GFCF typically show positive trends, their lack of statistical significance when subjected to stricter endogeneity controls (GMM) indicates that their impacts are not as strong or direct as those of other variables. The negligible effect of trade globalization indicates that, although it promotes the exchange of knowledge and technology, its direct impact on climate awareness might be overshadowed by other economic considerations.

While this study provides valuable insights, it is essential to acknowledge its limitations. We have used CRS as a proxy for climate awareness, which captures both preparedness and awareness against climate risks. Future research might benefit from establishing a dedicated climate awareness index. Furthermore, while our digitalization index covers many aspects of digital penetration, future research might look at more specific aspects of digitalization, such as the sorts of digital content consumed or the influence of certain digital platforms on climate awareness. Moreover, future research could stratify the data into different country groups and conduct comparative analyses—such as between developed versus developing nations—to provide more comprehensive insights into the relationship between digitalization and climate awareness.

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## **Does Digitalization Lead to Climate Awareness?**

*A Cross-Country Panel Data Analysis*

This paper explores how digitalization affects climate change awareness across 65 countries from 2005 to 2020. The study applies advanced econometric methods to uncover a U-shaped pattern that shows digitalization initially has little or negative impact, but significantly boosts awareness once digital maturity is reached. Renewable energy consumption has a similar pattern. Household consumption and corruption control enhance awareness, while human development, capital formation, and trade openness show negligible effects. The findings support targeted fiscal policies to improve digital infrastructure and boost climate awareness.

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