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Readiness, riskiness and renewables: Country-level readiness and innovation in renewable energy under macroeconomic uncertainty

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ABSTRACT

Readiness, riskiness, and renewables appear to form a "tripartite symbiosis" in the clean energy realm. Previous research underscores the significance of readiness as a prerequisite for a nation's advancement toward sustainable energy, urging careful navigation of uncertainties within this framework. Our research expands upon existing literature by delving into how country-level readiness influences a country's innovation in renewable energy in the face of uncertainty. Employing panel fixed effect threshold regression with four distinct models, we analyze this dynamic across 65 countries, representing both advanced and emerging economies. The results validate the presence of an uncertainty threshold effect across all model regressions, confirming a non-linear relationship among uncertainty, country-level readiness, and renewable energy innovation. Overall country-level readiness, along with its components—economic and social readiness—individually fosters renewable energy innovation under low uncertainty. However, this positive influence weakens as uncertainty exceeds the threshold. Conversely, governance readiness exerts a negative impact on renewable energy innovation under low uncertainty, with its detrimental effects becoming more significant at higher levels of uncertainty. The lagged uncertainty has a significant negative association with renewable energy innovation. Policymakers and investors should prioritize developing country level readiness to successfully manage the potential negative influence of uncertainties on renewable energy innovation.

1. Introduction

Our world is evolving fast toward a futuristic society distinguished by a robust science, technology and innovation ecosystem, aligning with the vision of Society 5.0 [1]. Renewable energy emerges as a pivotal component in this transition toward a sustainable future [2]. Driven by environmental degradation and normative pressures from global authorities, renewable energy has become a dominant trend in contemporary energy policies. As the energy sector shifts toward sustainability and low-carbon solutions, the critical role of renewable energy innovation is increasingly recognized [3,4]. Nevertheless, innovation within the renewable energy sector is inherently complex, shaped by key drivers such as the Kyoto Protocol, investments in research and development, and the expansion of renewable energy capacity. UN Trade and Development [5] underscores the positive impact of country-level technology readiness on renewable energy development, urging governments, businesses, and the international community to strengthen their capacity and readiness to fully capitalize on the opportunities presented by the emerging technological revolution. Fig. 1 confirms that country-level readiness drives renewable energy innovation.

While the national innovation ecosystem and its readiness are essential for renewable energy innovation, technological development and innovation almost always unfold in conditions of uncertainty. Such uncertainty can impose substantial constraints while also creating opportunities for technological innovation, especially in the context of radical and frontier technologies [6]. Given its amorphous nature, uncertainty appears to evolve over time, exerting a more significant macro-level impact on developing countries compared to developed

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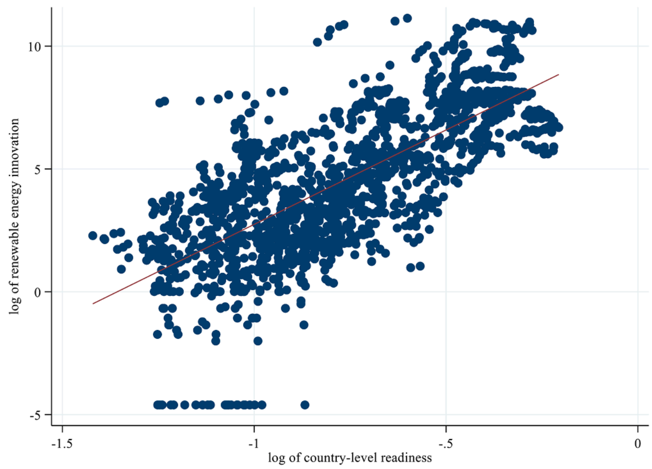

Fig. 1. Country-level readiness and renewable energy innovation for the study sample.
Source: Authors' construction.

ones, with particularly severe consequences in the short run [7]. Contemporary literature [8,9] examines the relationship between macro-level uncertainty and renewable energy innovation from both linear and non-linear perspectives, offering mixed evidence. Simultaneously, literature also offers policy prescriptions for enhancing country-level readiness to promote renewable energy innovation under conditions of uncertainty. However, there is limited understanding of how country-level readiness contributes to, or even whether and how it influences renewable energy innovation under uncertainty. Fig. 2 shows the non-linear relationship between world uncertainty and renewable energy innovation.

Building on this background, this study seeks to address this gap by examining the role of country-level readiness in driving renewable energy innovation across different uncertainty regimes. Our study directly addresses several United Nations Development Goals (SDGs), notably SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation and Infrastructure), and SDG 13 (Climate Action). First, by demonstrating how country-level readiness influences renewable energy innovation under uncertainty, we promote SDG 7.a (enhancing international cooperation to facilitate access to clean energy research and technology). Through heterogeneity analysis, we further elucidate how readiness differentially affects innovation across contexts, providing actionable insights for SDG 9.5 (enhancing scientific research, upgrade the technological capabilities of industrial sectors in all countries, in

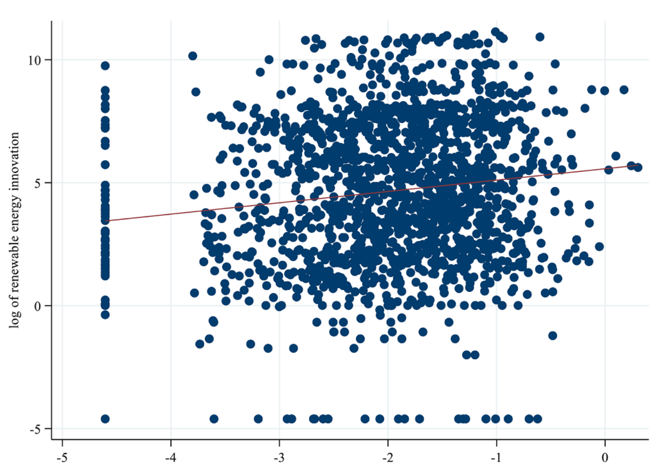

Fig. 2. World uncertainty and renewable energy innovation.
Source: Authors' construction.

particular developing countries). Finally, our findings support SDG 13.2, which emphasizes the integration of climate change measures into national policies and planning.

To this end, we analyze a panel dataset covering 65 countries, both advanced and emerging, from 1995 to 2020. We use patents related to environmental technologies as a measure of renewable energy innovation, as patents are widely recognized as a reliable indicator of technological sophistication and innovation [10,11]. Our patent data is sourced from the OECD patent database. To measure uncertainty, we utilize the World Uncertainty Index (WUI), developed by Ahir, Bloom & Furceri [12]. For country-level readiness, we utilize the ND-GAIN dataset [13], which has been available since 1995, specifically developed to measure a country's capacity for climate change adaptation. We apply the panel threshold regression model proposed by Hansen [14] to test whether and how renewable energy innovation is influenced by country-level readiness during times of uncertainty using uncertainty as the threshold variable and country-level readiness as the regime dependent variable.

Our study provides compelling evidence of threshold effect of uncertainty on the relationship between country-level readiness, including its individual dimensions of economic, governance, and social readiness and renewable energy innovation. The positive coefficient estimates for overall country-level readiness (2.43 to 2.01), economic readiness (0.89 to 0.65), and social readiness (2.89 to 2.46), along with the negative estimates for governance readiness (−1.83 to −2.4) are observed across the entire sample, with the effect varying from low to high uncertainty regimes. The lagged effect of uncertainty exhibits a significant negative association with renewable energy innovation in this study. Almost similar patterns emerge in country-group heterogeneity and post-Kyoto Protocol period threshold analyses, where a threshold effect is present. This study contributes to the literature by extending Hansen's [14] model to a novel and timely context-the interplay of uncertainty, country-level readiness, and renewable energy innovation.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature and highlights this study's contributions. Section 3 describes the research design, while Section 4 discusses the empirical results. Section 5 presents the discussions and future policy implications of the study. Section 6 concludes the paper.

2. Literature review

Empirical literature [15,16] identifies readiness as essential constructs for the development of emerging technologies and Education 4.0. Readiness is a multidimensional construct characterized by its multilevel effectiveness and dynamic, process-driven agility. Alternatively, readiness denotes complex interactions of parameters and conditionalities required to uptake a phenomenon [17]. Recognizing the significance of readiness for adaptation, the Notre Dame Global Adaptation Initiative asserts that country-level readiness is critical for leveraging investments for climate change adaptation [18].

Renewable energy as an adaptation strategy needs innovation to tackle more challenging sectors for decarbonization, such as long-haul transportation and energy-intensive industrial processes [19]. Effective climate change responses demand innovation, which represents human adaptation to evolving needs and socio-economic conditions, inherently rooted in social processes [20]. However, technological developments in advanced technologies are characterized by complexity and uncertainty [21]. The uneven distribution of technologies can be seen as a reflection of technology-related uncertainty [22]. New innovations in renewable energy cannot succeed without the support of entrepreneurs willing to act despite uncertainty [23]. The literature predominantly examines the impact of readiness and uncertainty on renewable energy innovation from a fragmented perspective, despite significant emphasis on their interconnections.

2.1. Renewable energy innovation and country-level readiness

Readiness is the current hymn in climate dialogue and a prime factor in attracting renewable energy technology investment to a country [24]. A country's readiness for renewable energy reflects its preparedness in terms of infrastructure, institutions, and human capital for the deployment and development of renewable energy sources. International Renewable Energy Agency (IRENA) defines renewables readiness assessment as "a comprehensive assessment of key conditions for renewable energy technology development and deployment in a country, and the actions necessary to further improve these conditions". In 2013, IRENA introduced its flagship policy program, 'Renewables Readiness Assessment (RRA)' to assist member nations in resource and technology development and the ability to scale up renewable energy [25].

Building readiness should be an ongoing process that fosters innovation and adaptation [26]. The knowledge production function framework explicitly considers infrastructure and institutions as a crucial component of technological innovation. Regions where knowledge externalities, including R&D, human capital, and university research, are significant tend to generate more knowledge than those where these factors are less prominent [27]. Empirical works [28,29] extensively highlight the importance of removing technological, financial and institutional barriers, alongside leveraging global support, to enhance countries' capacity for renewable energy innovation and development. Unfortunately, government supports and commitments to renewable energy research and development vary vastly across the globe [30]. Considering technological, social, political/regulatory, and economic dimensions across fourteen countries, it was found that Sweden has the most favorable conditions for renewable energy transition, followed by Western Europe and Canada [31]. Similarly, the United Arab Emirates (UAE) emerged as the most suitable country for renewable energy system development, with the Kingdom of Saudi Arabia (KSA) as the second-best choice in GCC countries [32].

Country-level systems and support significantly influence innovation and learning processes [33]. Empirical evidence demonstrates that public research and development expenditure positively contributes to the photovoltaic power generation (PV) innovation in Japan [34]. In China, the optimization of wind and solar innovation can be achieved by addressing technology readiness within long-term renewable energy planning [35]. While corruption does not appear to directly impact innovation, democratic institutions may foster a conducive environment for renewable energy innovation [36]. Scholars [37,38] also emphasize the importance of fostering both technical and societal conditions for developing renewable energy technologies to ensure the balanced diffusion of renewable energy systems within a country.

2.2. Renewable energy innovation and uncertainty

While renewable energy technology is environmentally friendly, it is also subject to uncertainty [39]. Renewable energy systems are particularly vulnerable to high levels of uncertainty [40], though it may stimulate longer-run innovation [7]. However, the recognition of uncertainty in technological innovation literature is limited. Recently, a group of scholars have begun to explore this dynamic, providing varied results. Energy policy uncertainty tends to suppress the overall renewable R&D investment while redirecting expenditures toward renewable energy efficiency research [41]. However, Bettarelli et al. [42] argue that increased uncertainty results in a long-term decline in green innovation, as reflected in the number of new green energy patent applications. Similarly, the negative impact of economic policy uncertainty on renewable energy innovation is observed across all quantiles in G7 countries [43]. In contrast, amid rising geopolitical risks and uncertainties, governments are scaling up investments in renewable energy research and development [44].

2.3. Emerging trends in renewable energy innovation, readiness and uncertainty

Recent advancements in renewable energy systems demand innovation driven by improved access to untapped energy resources, trends toward grid decentralization, the expansion of utility-scale energy storage, and the economic synergies of co-located, multi-purpose installations [45]. Virtual Power Plants (VPPs) address these evolving needs by providing a platform for competitive, renewable-based energy development that rivals traditional power plants in efficiency and flexibility [46]. Moreover, VPPs establish innovative economic incentive structures that benefit a range of stakeholders, including micro-DER owners, prosumers, and system operators, simultaneously accelerating renewable adoption and sustaining innovation in both technology and market design [47]. However, the integration of renewables into the energy mix introduces inherent supply-side uncertainty [48], compounded by broader macroeconomic and policy uncertainties. Therefore, comprehensive readiness, including targeted policy support, financial incentives, workforce training and public education is essential to foster technological innovation and improve interoperability across distributed energy systems [49].

So, the literature reveals a nonlinear relationship in the triadic association of renewable energy innovation, readiness, and uncertainty, which collectively drive structural adjustments over the long term. The impact of structural changes driven by readiness and uncertainty on renewable energy innovation has predominantly been examined in isolation, often within narrower scopes in the existing literature. However, a comprehensive joint analysis is essential, as readiness becomes particularly critical during times of crisis or uncertainty. Readiness encapsulates both the capacity and motivation necessary to effectively undertake tasks and adapt in complex informational environments and changing sociopolitical contexts [50]. Strategic readiness holds the potential to mitigate the systemic disruptions caused by uncertainty, providing a stabilizing framework for adaptive responses [51]. Based on this, we posit that country-level readiness will generally be positively associated with renewable energy innovation, though this relationship may weaken, become insignificant, or even turn negative in the presence of severe uncertainty.

Broadly, we can propose the following three hypotheses:

H_1: There is a threshold effect of uncertainty, beyond which the relationship between country-level readiness and renewable energy innovation changes.

H_2: In regimes of low uncertainty, country-level readiness contributes more to the renewable energy innovation.

H_3: In regimes of high uncertainty, the relationship between country-level readiness and green innovation weakens, becomes insignificant, or turns negative.

3. Model specification and data description

3.1. Renewable energy innovation

In this study, we utilize patents as a proxy for renewable energy innovation, sourcing patent data from the OECD patent database, renowned for its extensive and reliable coverage. Patents provide a robust measure for evaluating the external impact of knowledge internationally on domestic innovation [52]. Our analysis specifically focuses on the total number of patent applications related to environmental technologies.[2] Consistent with prior research [42,52], we examine patent applications rather than granted patents, as the process of granting patents is often prolonged and varies across countries. Furthermore, we link patents to the inventors' country of residence, as our focus is on the process of renewable energy knowledge generation at the national level. Our patent data is annual and spans from 1995 to 2020, encompassing a diverse range of advanced and emerging economies. Fig. 3 presents the annual total number of patents for all countries combined according to environmental technologies, included in our study since 1995. A list of the countries included in our analysis is provided in Appendix A.

3.2. Country-level readiness

The Notre Dame Global Adaptation Initiative (ND-GAIN) index provides country-level readiness scores for 190 countries annually since 1995. These scores measure a country's readiness for climate change adaptation, encompassing three key components: economic readiness, governance readiness, and social readiness. The overall readiness score ranges from 0 to 1, with higher values indicating greater adaptability to climate change. Economic readiness evaluates the investment climate and the capacity to mobilize private sector capital, using 10 indicators from the World Bank's *Doing Business* report. Governance readiness measures societal stability and institutional frameworks affecting investment risks, incorporating four indicators: political stability and absence of violence, control of corruption, rule of law, and regulatory quality. Social readiness assesses factors that enable efficient and equitable use of investments, based on four indicators: social inequality, ICT infrastructure, education, and innovation. The overall readiness score is derived by averaging the equally weighted scores of the three components, providing a comprehensive assessment of a country's capacity to utilize investments for adaptation. Detailed information on the methodology for calculating readiness is available on the ND-GAIN website.[3]

3.3. World uncertainty index

Our study uses country-level uncertainty data from the website of world uncertainty index.[4] The World Uncertainty Index is an instrument that tracks uncertainty worldwide by text mining the country reports that the Economist Intelligence Unit publishes. It is the first comprehensive attempt to create a panel of uncertainty indices for a broad range of both developed and developing nations. This index captures uncertainty arising from various economic and political events, encompassing both short-term factors (such as election-related uncertainty) and long-term issues (including the withdrawal of international forces from Afghanistan or tensions between North and South Korea). To ensure comparability across countries, the raw counts of uncertainty-related terms are normalized by the total word count in each report (measured in thousands of words). The annual average value of the index is used as a proxy for uncertainty in our study. Full disclosures on the index are available on the website of the World Uncertainty Index.

3.4. Control variables

This study controls three key variables influencing renewable energy innovation, drawing from previous research. First, renewable energy technologies, like other emerging technologies, require substantial investment and face lengthy, uncertain development processes [53]. As a result, high-income countries (GDP) are expected to have a stronger positive impact on renewable energy innovation [54]. Conversely, economic growth (GDP) may present challenges to renewable energy innovation within the framework of sustainable development [55]. Secondly, international trade can facilitate access to high-quality, reliable, and cost-effective technologies while also exposing countries to institutional pressures to adopt sustainable practices. Trade stimulates domestic innovation in renewable energy by channeling signals of increasing environmental stringency from outside [56]. Thirdly, CO_2 emissions are the primary driver of global warming, underscoring the critical need for renewable energy. The innovation process in renewable energy represents an active and strategic response to climate change [57]. GDP per capita (PPP, constant 2017$) and trade openness data are sourced from the World Bank, while carbon emissions per capita data is obtained from Our World in Data.

3.5. Study design

The study uses the panel threshold regression models, as proposed by Hansen [14] to capture the non-linear relationship in the triadic interplay among renewable energy innovation, country-level readiness and uncertainty. The model identifies distinct regimes based on a threshold variable, allowing the effects of key explanatory variables to vary across regimes. Such a method is particularly suited to analyzing relationships that are influenced by structural changes in contextual factors such as macroeconomic conditions, policy environments, or external shocks [58,59]. Under the model, for a balanced panel data set $\{y_{it}, q_{it}, x_{it}: 1 \leq i \leq n,\ 1 \leq t \leq T\}$, the single threshold regression model is given by:

$$Y_{it} = \mu_i + \beta_1 x_{it} I(q_{it} \leq \gamma) + \beta_2 x_{it} I(q_{it} > \gamma) + \sum_{k=3}^{K} \beta_k R_{it} + \mathrm{e}_{it} \tag{1}$$

The corresponding indicator functions for the single threshold model are defined as follows:

$$\mathrm{I}(\mathrm{q}_{it} \leq \gamma) = \begin{cases} 1, & \text{if } q_{it} \leq \gamma \\ 0, & \text{if } q_{it} > \gamma \end{cases}; \quad \mathrm{I}(\mathrm{q}_{it} > \gamma) = \begin{cases} 1, & \text{if } q_{it} > \gamma \\ 0, & \text{if } q_{it} \leq \gamma \end{cases}$$

The subscript i denotes the individual, and t represents the time. The variable y_{it} is the dependent variable, while μ_i captures the unobserved individual-specific effect, reflecting the individual's fixed effect. x_{it} represents the k-dimensional vector explanatory variable, and q_{it} is the threshold variable. The function I(.) is the indicator function, which takes the value of 1 when the condition is met and 0 otherwise. R_{it} is the set of control variables, and e_{it} is the error term, assumed to follow an independent and identically distributed process. The individual effects are removed by subtracting the group-specific mean from each observation in the model. The transformed version of Eq. (1) is:

$$y'_{it} = \beta_1 x'_{it} I(q_{it} \leq \gamma) + \beta_2 x'_{it} I(q_{it} > \gamma) + \sum_{k=3}^{K} \beta_k R_{it} + \mathrm{e}'_{it} \tag{2}$$

The data are then aggregated and stacked across all individuals and expressed as:

$$\mathrm{Y}* = \mathrm{X}*(\gamma)\beta + \mathrm{e}* \tag{3}$$

For any given threshold γ, the slope coefficient β can be estimated using ordinary least squares (OLS) for long-term estimation. The estimation equation is given by:

$$\widehat{\beta}(\gamma) = (\mathrm{X}^*(\gamma)'\mathrm{X}^*(\gamma))^{-1}\mathrm{X}^*(\gamma)'\mathrm{Y}^* \tag{4}$$

[2] The environment technologies considered in this study are:1-Capture, storage, sequestration or disposal of greenhouse gases; 2-Climate change mitigation technologies in the production or processing of goods; 3-Climate change mitigation technologies related to buildings; 4-Climate change mitigation technologies related to energy generation, transmission or distribution; 5-Climate change mitigation technologies related to transportation; 6-Cclimate change mitigation technologies related to wastewater treatment or waste management; 7-Environmental management.

[3] https://gain.nd.edu/our-work/country-index/

[4] https://worlduncertaintyindex.com/

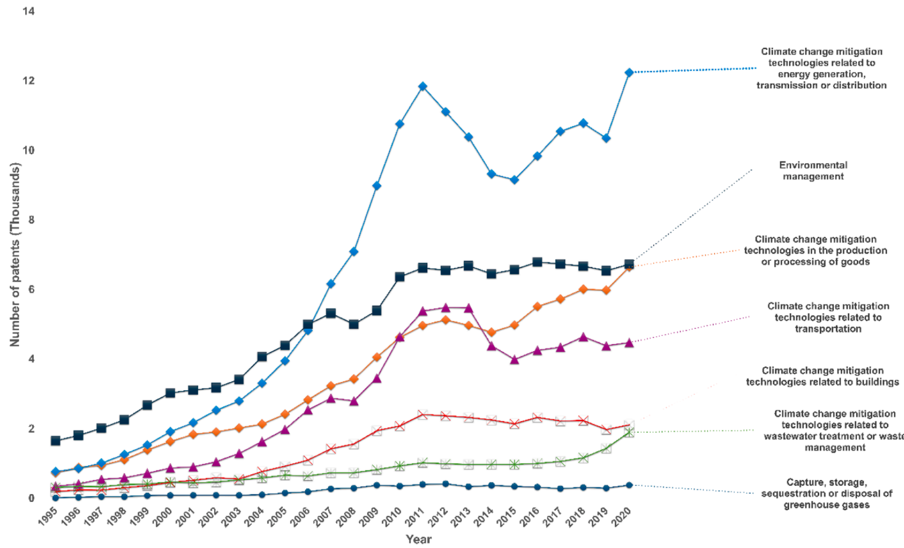

Fig. 3. Evolution of patents across environment technology groups.
Source: Authors' construction

The corresponding vector of regression's residual is: $\hat{e}^*(\gamma) = Y^*\text{-}X^*(\gamma)\,\hat{\beta}\,(\gamma)$ and the residual sum of squares is then computed as: $S_1(\gamma) = \hat{e}^*(\gamma)'\hat{e}^*(\gamma)$. The model works by using bootstrap methods to identify threshold effects, approximating the distribution under the null hypothesis. This enables researchers to derive sample-specific critical values for detecting the threshold. The threshold effect test is sequential, ranging from a single threshold to multiple thresholds, with a focus on testing the equality of coefficients between adjacent regimes. The likelihood ratio test statistics, as proposed by the model, are as follows:

For single threshold effect, $(H_1 : \beta_1 = \beta_2, H_1' : \beta_1 \neq \beta_2), F_1$
$$= \frac{S_0(\gamma) - S_1(\hat{\gamma})}{\hat{\sigma}_1^2} \tag{5}$$

For double threshold effect, $(H_2 : \beta_1 = \beta_2, H_2' : \beta_1 \neq \beta_2), F_2$
$$= \frac{S_1(\gamma) - S_2(\hat{\gamma})}{\hat{\sigma}_2^2} \tag{6}$$

For triple threshold effect, $(H_3 : \beta_1 = \beta_2,\ H_3' : \beta_1 \neq \beta_2),\ F_3$
$$= \frac{S_2(\gamma) - S_3(\hat{\gamma})}{\widehat{\sigma_3}^2} \tag{7}$$

Here, the F statistic follows a nonstandard asymptotic distribution which dominates chi-square distribution. S_0 represents the sum of squared residuals without a threshold, while S_1, S_2 and S_3 correspond to models with one, two and three thresholds, respectively. $\widehat{\sigma_1}^2$, $\widehat{\sigma_2}^2$, $\widehat{\sigma_3}^2$ are the variance estimates of the error terms in the single, double, and triple threshold models. A significant result indicates that the threshold effect is important for explaining the relationship between the variables.

After identifying the threshold effect, it is important to check that the threshold estimator is consistent and that its asymptotic distribution is non-standard, which is a characteristic of the likelihood ratio (LR) test in threshold regression. The LR test ratios, as proposed by the model are as follows:

For single threshold model, $(H_1 : \gamma = \gamma_0,\ H_1' : \gamma \neq \gamma_0),\ LR_1$
$$= \frac{S_1(\gamma) - S_1(\hat{\gamma})}{\widehat{\sigma_1}^2} \tag{8}$$

For double threshold model, $(H_2 : \beta_1 = \beta_2,\ H_2' : \beta_1 \neq \beta_2),\ LR_2$
$$= \frac{S_2(\gamma) - S_2(\hat{\gamma})}{\widehat{\sigma_2}^2} \tag{9}$$

For triple threshold model, $(H_3 : \beta_1 = \beta_2,\ H_3' : \beta_1 \neq \beta_2),\ LR_3$
$$= \frac{S_3(\gamma) - S_3(\hat{\gamma})}{\widehat{\sigma_3}^2} \tag{10}$$

The terms $S_1(\gamma)$, $S_2(\gamma)$, and $S_3(\gamma)$ represent the residual sum of squares for models with a fixed threshold γ in single, double and triple threshold specifications, respectively. In contrast, $S_1(\widehat{\gamma_1})$, $S_2(\widehat{\gamma_2})$, and $S_3(\widehat{\gamma_3})$ denote the residual sum of squares for models with estimated threshold values $\widehat{\gamma_1}$, $\widehat{\gamma_2}$ and $\widehat{\gamma_3}$, in the single double and triple threshold models, respectively. Similarly, $\widehat{\sigma_1}^2\widehat{\sigma_2}^2$, and $\widehat{\sigma_3}^2$ indicate the estimated variances of the residuals for the corresponding threshold models.

When multiple threshold effects are present in the model, the single threshold regression in Eq. (1) can be generalized to accommodate multiple thresholds. For example, the double threshold regression model can be expressed as follows:

$$y_{it} = \mu_i + \beta_1 x_{it} I(q_{it} \leq \gamma_1) + \beta_2 x_{it} I(\gamma_1 < q_{it} \leq \gamma_2) + \beta_3 x_{it}(\gamma_2 < q_{it}) + \sum_{k=4}^{K} \beta_k R_{it} + e_{it} \tag{11}$$

The values γ_1 and γ_2 represent the threshold parameters that divide the equation into three distinct regimes, with the condition that $\gamma_1 < \gamma_2$.

Our study aims to elucidate the dynamic effects of country-level readiness under conditions of uncertainty on renewable energy innovation using panel data. Our baseline regression that can be used to verify the linear and non-linear relationship between country-level readiness, uncertainty and green energy innovation is as follows:

$$lnINV_{it} = \mu_i + \beta_1 lnRN_{it} + \beta_2 lnUT_{it} + \beta_3 lnCE_{it} + \beta_4 lnGDP_{it} + \beta_5 lnTRO_{it} + e_{it} \tag{12}$$

$$lnINV_{it} = \mu_i + \beta_1 lnERN_{it} + \beta_2 lnGRN_{it} + \beta_3 lnSRN_{it} + \beta_4 lnUT_{it} + \beta_5 lnCE_{it} + \beta_6 lnGDP_{it} + \beta_7 lnTRO_{it} + e_{it} \tag{13}$$

The above fixed effects model includes key variables: country-level renewable energy innovation (*lnINV),* country-level overall readiness (*lnRN*) and uncertainty (*lnUT*), alongside control variables: carbon emissions (*lnCE*), GDP (*lnGDP*), and trade openness (*TRO*). Country-level overall readiness can be further disaggregated into its constituents: economic (*lnERN*), governance (*lnGRN*), and social (*lnSRN*). Following Hansen's [14] recommendation to use an exogenous variable as the threshold, we employ the first lag of uncertainty as the threshold variable, since uncertainty often affects outcomes with a lag. The first lags of country-level readiness and its components serve sequentially as the regime-dependent variables, while the remaining explanatory variables are regime-independent. Thus, our four final panel threshold regression models are as follows:

$$ln\ INV_{it} = \mu_1 + \beta_1 ln\ UT_{it} + \beta_2 ln\ UT_{it-1} + \beta_3 ln\ CE_{it} + \beta_4 ln\ GDP_{it} + \beta_5 TRO_{it} + \beta_6 ln\ RN_{it-1} I(ln\ UT_{it-1} \le \gamma_1) + \beta_7 ln\ RN_{it-1} I(\gamma_1 < ln\ UT_{it-1} \le \gamma_2) + \beta_8 ln\ RN_{it-1} I(\gamma_2 < ln\ UT_{it-1}) + e_{it} \tag{14}$$

$$ln\ INV_{it} = \mu_1 + \beta_1 ln\ UT_{it} + \beta_2 ln\ UT_{it-1} + \beta_3 ln\ CE_{it} + \beta_4 ln\ GDP_{it} + \beta_5 TRO_{it} + \beta_6 ln\ ERN_{it-1} I(ln\ UT_{it-1} \le \gamma_1) + \beta_7 ln\ ERN_{it-1} I(\gamma_1 < ln\ UT_{it-1} \le \gamma_2) + \beta_8 ln\ ERN_{it-1} I(\gamma_2 < ln\ UT_{it-1}) + e_{it} \tag{15}$$

$$lnINVV_{it} = \mu_1 + \beta_1 ln\ UT_{it} + \beta_2 ln\ UT_{it-1} + \beta_3 ln\ CE_{it} + \beta_4 ln\ GDP_{it} + \beta_5 TRO_{it} + \beta_6 ln\ GRN_{it-1} I(ln\ UT_{it-1} \le \gamma_1) + \beta_7 ln\ GRN_{it-1} I(\gamma_1 < ln\ UT_{it-1} \le \gamma_2) + \beta_8 ln\ GRN_{it-1} I(\gamma_2 < ln\ UT_{it-1}) + e_{it} \tag{16}$$

$$ln\ INV_{it} = \mu_1 + \beta_1 ln\ UT_{it} + \beta_2 ln\ UT_{it-1} + \beta_3 ln\ CE_{it} + \beta_4 ln\ GDP_{it} + \beta_5 TRO_{it} + \beta_6 ln\ SRN_{it-1} I(ln\ UT_{it-1} \le \gamma_1) + \beta_7 ln\ SRN_{it-1} I(\gamma_1 < ln\ UT_{it-1} \le \gamma_2) + \beta_8 ln\ SRN_{it-1} I(\gamma_2 < ln\ UT_{it-1}) + e_{it} \tag{17}$$

Fig. 4 synthesizes the key methodological procedures and robustness tests applied in this study.

This empirical framework is designed to enhance methodological rigor by systematically addressing key econometric challenges. To ensure full reproducibility, the estimation specifications and parameter settings are presented in detail in the relevant subsections of the following empirical results section. Specifically, we implement the panel threshold estimation based on Hansen's [14] fixed effects model, using Stata 18.0. The procedure follows the command developed by Wang [60], with 300 bootstrap replications, a grid size of 400, and a 10 % trimming at both ends to ensure robust estimation of the threshold parameter. Bootstrap estimates may vary slightly across runs; our results remain largely stable and consistent across multiple iterations without imposing a fixed seed. For LR statistic visualization, we employ the _matplot visualization code provided by Wang [60], adapted for the purposes of this study.

4. Empirical results

Table 1 summarizes the descriptive statistics of the study's key variables. Notably, two key variables, lnINV (min=−4.61, max=11.13) and lnUT (min=−4.6, max = 0.30) exhibit considerable range and skewness, which supports the use of threshold regression. Moreover, lnRN with near-zero skewness (0.02) and moderate kurtosis (1.97), facilitating stable regime-specific coefficient estimation. Moderate standard deviations across variables indicate manageable within-panel heterogeneity, justifying a panel-based approach. To satisfy the requirements of panel fixed effect threshold regression, 0.01 is added to the uncertainty and renewable energy innovation variables with zero values-a standard approach in similar econometric studies [61]. Table 2 summarizes cross-sectional dependence and panel unit root tests results. The CD test and the Breusch-Pagan LM test (x^2 = 12,328.326, $p <$ 0.001) confirms the presence of cross-sectional dependence in all variables except country-level governance readiness, justifying the use of second-generation panel unit root tests, specifically Pesaran CIPS and CADF, to assess stationarity. The results indicate all variables are stable and integrated at $I(1)$. The Pedroni cointegration test (Table 3) confirms a significant long-run equilibrium relationship among the variables at 1 % level, both with and without a trend. The data stability analysis, including panel unit root and cointegration tests, is outlined in Appendix B.

4.1. Panel threshold effect estimation

Following Wang [60], we set the bootstrap frequency to 300 and the grid size to 400, with a 95 % confidence interval and a 10 % trimming rate for robust threshold estimation. Clustered robust standard errors are applied to address heteroscedasticity and autocorrelation [62]. The double threshold model is applied when its statistical significance is established ($p < 0.10$).

4.1.1. Panel threshold effect estimation (full sample)

As shown in Table 4, the F-statistics for the single and double threshold effects in Model (1), which are 30.79 and 21.61, respectively, both significant at the 1 % level. The dual threshold values (−2.9266,

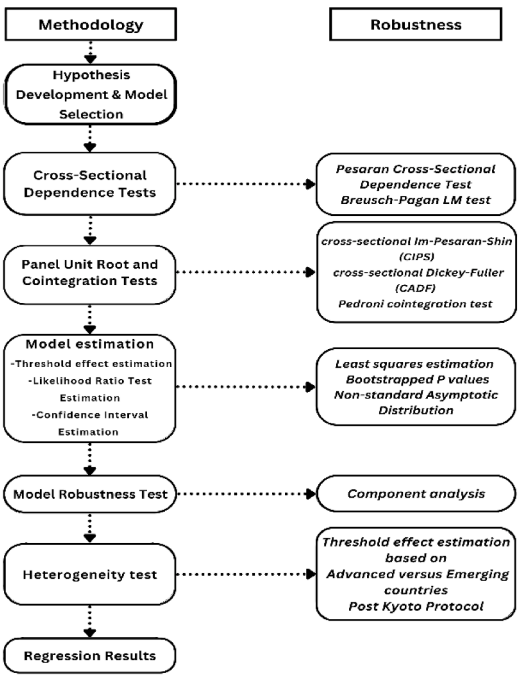

Fig. 4. Simplified workflow of the methodology and robustness assessment.
Source: Authors' construction

−1.7983) yield a lower residual sum of squares compared to the single threshold value (−2.4289), confirming the significant double threshold effect of uncertainty on renewable energy innovation when considering country-level overall readiness. After removing the logarithmic transformation, the double threshold values are 0.0535 and 0.1655. Model (2) examines the threshold effect of uncertainty on renewables innovation regarding country-level economic readiness, with both single (−2.4289) and double (−2.6363, −1.7983) thresholds significant at the 1 % level. The transformed dual threshold values are 0.0716 and 0.1655 respectively. In Model (3), the uncertainty threshold effect related to country-level governance readiness reveals a significant single threshold effect (F-statistic=37.17, $p < 0.01$) and a less significant double threshold effect (F-statistic=17.10, $p < 0.05$). Despite the lower significance, the double threshold values (−2.9266, −1.8261) better captures the dynamics of the relationship, with the corresponding transformed threshold values being 0.0535 and 0.1610. In Model (4), the uncertainty threshold effect related to country-level social readiness shows significant single (−2.4459) and double threshold estimates (−2.4459, −1.8261) at the 1 % and 10 % levels, respectively. The corresponding transformed thresholds values are 0.0866 and 0.1610.

Table 2
Cross-sectional dependency (CD) and panel unit root tests.

Variables	CD	CIPS I(0)	CIPS I(1)	CADF I(0)	CADF I(1)
$lnINV_{it}$	175.521***	−3.187***	–	−2.398***	–
$lnRN_{it}$	121.538***	−2.343***	–	−1.613	−2.375***
$lnRN_{it-1}$	117.8***	−2.414***	–	−1.666	−2.352***
$lnERN_{it}$	75.041***	−2.865***	–	−2.028***	–
$lnERN_{it-1}$	73.299***	−2.861***	–	−2.064***	–
$lnGRN_{it}$	0.15	−1.461	−4.145***	−1.298	−2.434***
$lnGRN_{it-1}$	0.083	−1.518	−4.044***	−1.293	−2.363***
$lnSRN_{it}$	194.083***	−2.256***	–	−2.202***	–
$lnSRN_{it-1}$	191.695***	−2.204***	–	−2.178***	–
$lnUT_{it}$	34.584***	−3.920***	–	−2.580***	–
$lnUT_{it-1}$	30.984***	−3.829***	–	−2.494***	–
$lnCE_{it}$	16.496***	−1.650	−4.703***	−1.215	−2.380***
$lnGDP_{it}$	195.934***	−2.303***	–	−2.387***	–
$lnTRO_{it}$	60***	−1.635	−3.943***	−1.511	−2.614***

Note: The figures represent t-statistic values, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 3
Pedroni panel cointegration test results.

	No Trend		Trend	
	Statistic	p-Value	Statistic	p-Value
Modified Phillips-Perron t	7.0795	0.0000	8.1777	0.0000
Phillips-Perron t	−8.0098	0.0000	−9.6145	0.0000
Augmented Dickey-Fuller t	−8.7025	0.0000	−9.2754	0.0000

To visually support the threshold estimation, Fig. 5 presents the likelihood ratio (LR) function plots for the four final regression models using the full sample. Each threshold corresponds to the point where the LR statistic equals zero, with the 95 % confidence interval shown below the dotted line. All models identify significant double threshold effects, producing two plots per model that illustrate the first and second threshold points and confirm significant regime shifts.

4.1.2. Panel threshold effect estimation (sub sample)

Following the classification outlined by the International Monetary Fund in the World Economic Outlook [63], we divide the full sample of countries into two sub-samples: advanced economies and emerging economies. In Table 5**,** for advanced economies, Model (1) yields F-statistics of 16.84 (single threshold) and 13.88 (double threshold), both exceeding the critical values at the 5 % level.

The dual threshold values (−2.4992, −1.4071) after transformation are 0.0821 and 0.2448. In Model (2), the single (−2.7074) and double (−2.7074, −1.4071) threshold estimations are significant at the 10 % level, with transformed double threshold values of 0.0667 and 0.2448. Model (3) shows a significant double threshold effect (−2.7074,−1.4417) at the 5 % level, with transformed threshold values

Table 1
Descriptive statistics.

Variables	Obs	Mean	S.D.	Min	Max	Median	Skew.	Kurt.
$lnINV_{it}$	1690	4.663	2.951	−4.605	11.137	4.666508	−0.237	3.059
$lnRN_{it}$	1690	−0.751	.281	−1.421	−0.206	−0.758777	0.023	1.977
$lnRN_{it-1}$	1625	−0.753	.281	−1.421	−0.206	−0.764689	0.033	1.978
$lnERN_{it}$	1690	−0.78	.277	−2.38	−0.127	−0.804602	−0.304	4.95
$lnERN_{it-1}$	1625	−0.783	.277	−2.38	−0.127	−0.808157	−0.305	5.048
$lnGRN_{it}$	1690	−0.586	.322	−1.449	−0.108	−0.542917	−0.302	2.056
$lnGRN_{it-1}$	1625	−0.586	.323	−1.449	−0.108	−0.543000	−0.3	2.047
$lnSRN_{it}$	1690	−0.983	.454	−2.346	−0.233	−0.941246	−0.326	2.167
$lnSRN_{it-1}$	1625	−0.99	.457	−2.346	−0.239	−0.952639	−0.308	2.141
$lnUT_{it}$	1690	−1.962	.892	−4.605	.302	−1.85112	−0.812	3.935
$lnUT_{it-1}$	1625	−1.986	.892	−4.605	.302	−1.87603	−0.788	3.892
$lnCE_{it}$	1690	1.515	.893	−1.618	3.058	1.74832	−0.705	2.992
$lnGDP_{it}$	1690	9.885	.801	7.651	11.497	9.99658	−0.431	2.341
$lnTRO_{it}$	1690	−0.350	.509	−1.80	1.47	−0.381396	.334	3.700

Note: All variables are log-transformed. SD = Standard Deviation, Skew. = Skewness, Kurt. = Kurtosis.

Table 4
Threshold effect test results (full sample).

Threshold models	No. of Thresholds	F value	P value	Critical Value			Threshold value	95 % confidence interval
				1 %	5 %	10 %		
Model 1	Single	30.79***	0.000	16.873	13.695	11.402	−2.4289	−2.4512,−2.4215
$lnRN_{it-1}$	Double	21.61***	0.000	13.732	11.016	9.630	−2.9266	−2.9316,−2.9225
							−1.7983	−1.8267,−1.7926
Model 2	Single	19.30***	0.003	16.849	13.366	11.039	−2.4289	−2.4512,−2.4215
$lnERN_{it-1}$	Double	17.84***	0.006	16.831	11.680	9.658	−2.6363	−2.6536,−2.6360
							−1.7983	−1.8267,−1.7926
Model 3	Single	37.17***	0.000	24.197	16.013	11.882	−2.4289	−2.4512,−2.4215
$lnGRN_{it-1}$	Double	17.10**	0.013	19.113	12.394	10.191	−2.9266	−2.9316,−2.9225
							−1.8261	−1.8523,−1.8201
Model 4	Single	24.52***	0.003	17.148	15.270	12.225	−2.4459	−2.4780,−2.4365
$lnSRN_{it-1}$	Double	11.81*	0.043	19.374	12.094	10.073	−2.4459	−2.4790,−2.4365
							−1.8261	−1.8523,−1.8201

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

of 0.0667 and 0.2365. In contrast, no threshold effect is observed in Model (4) for advanced economies, indicating a linear relationship between uncertainty, country-level social readiness and renewable energy innovation. Fig. 6 presents the likelihood ratio (LR) function plots for the threshold effects estimated in advanced economies. Regression Models 1 to 3, each generate two LR plots corresponding to the estimated double threshold effects. These plots exhibit clear dips at their respective threshold values, confirming the existence of statistically significant regime changes. No threshold effect is identified for Model 4 in advanced economies.

In Table 6 for emerging economies, Model (1) shows significant single (−2.4327) and double (−2.9254, −1.7753) threshold effects at the 1 % level. The transformed threshold values are 0.0536. and 0.1694. In Model (2), the double threshold effects (−2.9254,−1.8308) are significant at the 1 % level, with transformed values of 0.0536 and 0.1602. Model (3) shows a statistically significant single threshold at −2.4459 and a double threshold at −2.8944 and −1.7580, which is selected based on significance at the 10 % level. The corresponding transformed threshold estimates values are 0.0553 and 0.1723, respectively. In contrast, Model (4) exhibits only single (−2.4459) threshold effect significantly at the 5 % level, with logarithmically transformed threshold value of 0.0866. Fig. 7 displays the likelihood ratio (LR) function plots for the threshold estimations in emerging economies. For Models 1 to 3, each regression model produces two LR plots, corresponding to the estimated double threshold effects. These plots reveal distinct dips at the respective threshold values, confirming the presence of statistically significant regime shifts. In contrast, Model 4 supports only a single threshold defect and accordingly, displays a single LR plot.

4.1.3. Panel threshold effect estimation (post Kyoto Protocol period)

The Kyoto Protocol-an important milestone in international climate policy-entered into force in 2005. This study further examines whether and how uncertainty generates threshold effects on renewable energy innovation, considering overall country-level readiness in the post-Kyoto Protocol period. As shown in Table 7, uncertainty, together with overall readiness, produces a single threshold effect on renewable energy innovation for the full sample, with a threshold value of −1.7826.

After removing the logarithmic transformation, this corresponds to a threshold of 0.1682. A double threshold (−2.4742, −1.2465) effect is observed for advanced economies during the same period, with transformed threshold values of 0.0842 and 0.2875, while no significant threshold effect is identified for emerging economies. Fig. 8 presents the likelihood ratio (LR) function plots for the threshold estimations during the post-Kyoto Protocol period. For the whole sample, the LR plot indicates a significant single threshold effect. In contrast, for advanced economies, Model 1 exhibits significant double threshold effects, confirming the presence of distinct regime shifts during this period.

4.2. Results of panel threshold regression

4.2.1. For the full sample

Table 8 presents the findings of the panel threshold regression for the full sample. The results indicate that the first lag of uncertainty has a statistically significant negative association with renewable energy innovation across all models, except Model (4). Among the control variables, GDP consistently exhibits a positive and statistically significant impact at the 1 % level across all specifications on renewable energy innovation. The effect of trade openness is also positive but achieves statistical significance only in the context of a country's economic and governance readiness levels on renewable energy innovation.

From a threshold perspective, Model (1) reveals that when uncertainty is below 0.0535, country-level overall readiness has a positive and statistically significant effect on renewable energy innovation, with a coefficient of 2.44. As uncertainty increases to the second stage (0.0535–0.1655), this effect declines to 2.01 and further decreases to 1.64 at the third stage (above 0.1655), consistent with the study's hypotheses. In Model (2), which focuses on economic readiness, a similar pattern emerges. When uncertainty is below 0.0716, country-level economic readiness positively and significantly influences renewable energy innovation, with a coefficient of 0.89. However, as uncertainty rises to the second stage (0.0716–0.1655), the effect diminishes to 0.64 and further decreases in the third stage (above 0.1655). In contrast, Model (3) demonstrates that country-level governance readiness negatively affects renewable energy innovation under uncertainty. When uncertainty is below 0.0535, the impact is −1.83; this negative effect intensifies to −2.48 as uncertainty increases to the second stage (0.0535–0.1610), but moderates to −1.61 in the third stage (above 0.1610). Finally, Model (4) shows that country-level social readiness at the country level positively contributes to renewable energy innovation. When uncertainty is low (below 0.0866), the coefficient is 2.89, but as uncertainty rises to the second stage (0.0866–0.1610), the coefficient decreases to 2.68 and further drops to 2.46 in the third stage (above 0.1610).

4.2.2. For the sub-sample

Table 9 presents the panel threshold regression results for advanced economies. The first lag of uncertainty negatively impacts renewable energy innovation, while current uncertainty shows no significant effect. GDP per capita has a positive, statistically significant relationship with innovation, while trade openness only significantly impacts innovation at the economic and governance readiness levels. From a threshold perspective, Model (1) shows that when uncertainty is below 0.0821, overall country readiness significantly boosts innovation, with a coefficient of 3.17. This effect declines to 2.81 as uncertainty rises to the second stage (0.0821–0.2448) and increases to 4.05 in the third stage (above 0.2448). In Model (2), economic readiness significantly

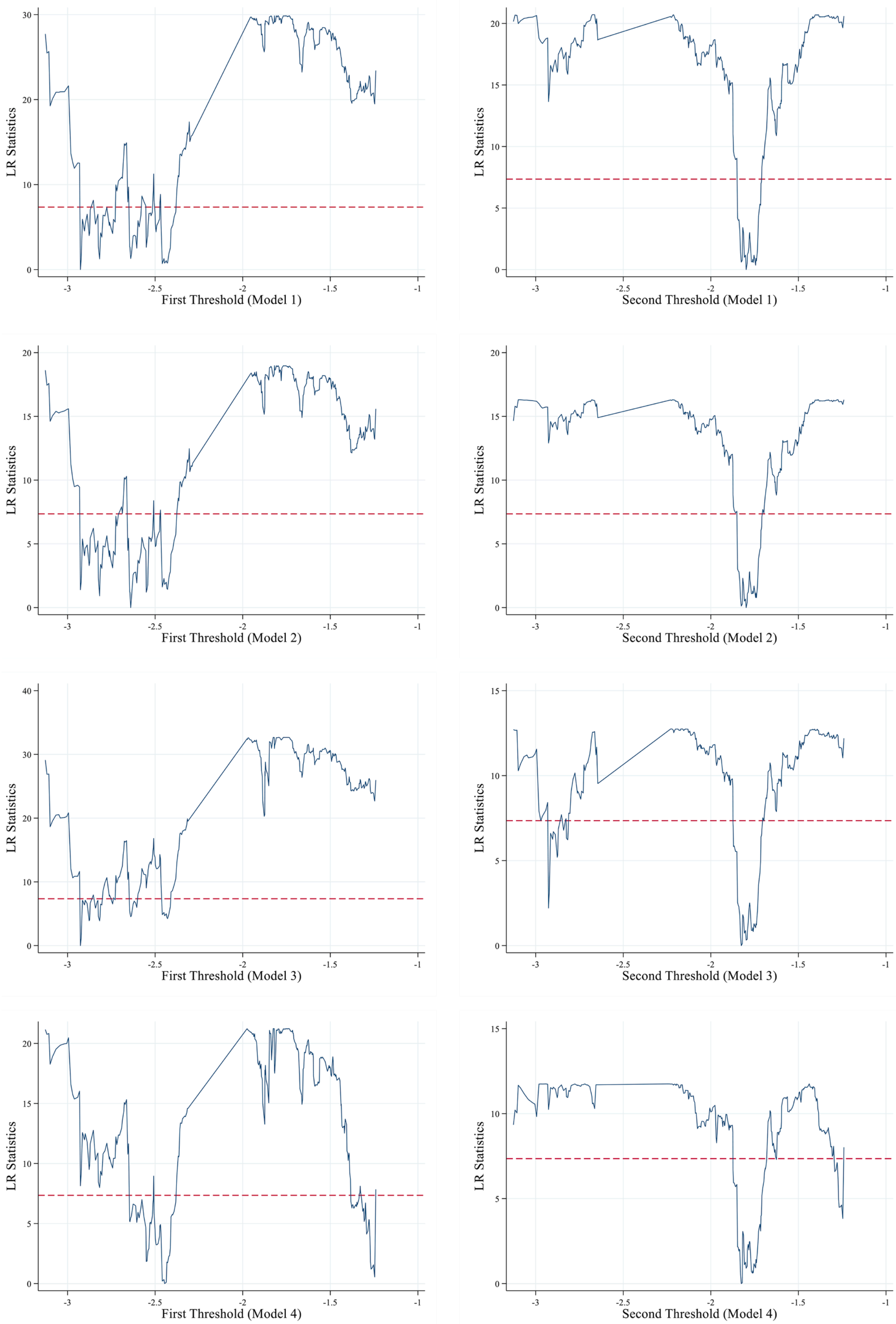

Fig. 5. LR diagrams with estimated threshold values (full sample).

Table 5
Threshold effect test results (advanced economies).

Threshold models	No. of Thresholds	F value	P value	Critical Value 1 %	5 %	10 %	Threshold value	95 % confidence interval
Model 1	Single	16.84**	0.016	18.713	13.543	11.421	−2.4992	−2.5482, −2.4877
$lnRN_{it-1}$	Double	13.88**	0.036	15.688	12.965	10.793	−2.4992	−2.5316, −2.4877
							−1.4071	−1.5436, −1.4059
Model 2	Single	13.40*	0.070	17.865	14.295	12.058	−2.7074	−2.7380, −2.7057
$lnERN_{it-1}$	Double	12.87*	0.096	17.865	14.660	12.480	−2.7074	−2.7232, −2.7057
							−1.4071	−1.5491, −1.4059
Model 3	Single	11.35	0.113	16.176	13.855	11.899	−2.7074	−2.7263, −2.7057
$lnGRN_{it-1}$	Double	11.93**	0.046	16.685	11.610	9.9595	−2.7074	−2.7232, −2.7057
							−1.4417	−1.6602, −1.4386

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

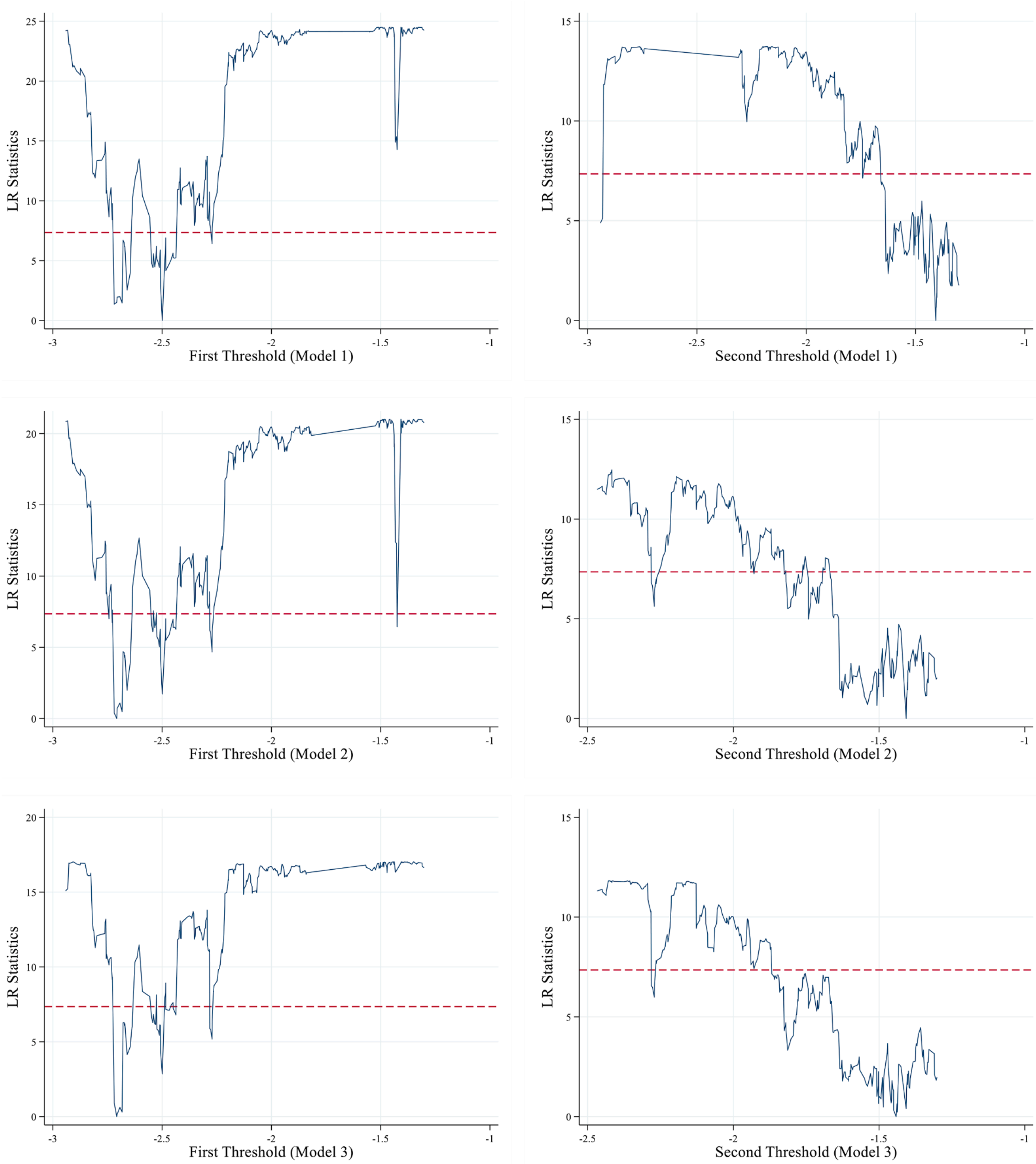

Fig. 6. LR diagrams with estimated threshold values (advanced economies).

Table 6
Threshold effect test results (emerging economies).

Threshold models	No. of Thresholds	F value	P value	Critical Value			Threshold value	95 % confidence interval
				1 %	5 %	10 %		
Model 1	Single	19.51***	0.000	15.514	11.532	9.454	−2.4327	−2.4529,−2.4187
$lnRN_{it-1}$	Double	16.09***	0.006	17.376	11.651	8.883	−2.9254	−2.9533,−2.9208
							−1.7753	−1.8271,−1.7620
Model 2	Single	13.21**	0.036	19.330	11.722	9.558	−2.4327	−2.4706,−2.4174
$lnERN_{it-1}$	Double	13.44***	0.000	10.834	9.338	8.204	−2.9254	−2.9683,−2.9208
							−1.8308	−1.8554,−1.8198
Model 3	Single	22.24***	0.000	16.056	13.093	10.820	−2.4459	−2.6152,−2.4017
$lnGRN_{it-1}$	Double	9.94*	0.066	15.790	10.777	9.008	−2.8944	−2.9912,−2.8456
							−1.7580	−1.9297,−1.7349
Model 4	Single	16.58**	0.040	19.791	15.841	12.728	−2.4459	−2.5556,−2.4329
$lnSRN_{it-1}$	Double	9.94	0.126	18.869	12.176	10.903	−1.2502	−1.3295,−1.2491

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; for Model 3 only, grid (75) is used to produce stable threshold value.

contributes to innovation when uncertainty is below 0.0667, with a coefficient of 0.84. As uncertainty rises, the coefficient effect decreases but increases at the third stage (above 0.2449). In Model (3), governance readiness does not significantly affect innovation until uncertainty exceeds the second threshold of 0.2365, at which point the impact becomes significantly negative (−1.97) at the 10 % level. Table 10 presents the panel threshold regression results for emerging economies.

Like previous findings, the lagged uncertainty has statistically significant negative association with renewable energy innovation in emerging economies . Off all control variables, GDP per capita positively contributes to the renewable energy innovation at 1 % significance across all regression models. From a threshold perspective, in Model (1), when uncertainty is below 0.0536, country level readiness contributes positively to the renewable energy innovation significantly with a coefficient of 2.56 in the emerging economy. As uncertainty increases to the second stage (0.0536 to 0.1694), the coefficient decreases to 1.93. It goes down further to 1.470 when uncertainty reaches (above 0.1694). For Model 2, we see economic readiness positively contributes to the renewable energy innovation in emerging economies. When uncertainty is below the first threshold (0.0536), the coefficient estimate is 0.96, when uncertainty moves to the next level (0.0536 to 0.1602), the coefficient estimate decreases to 0.35 and when uncertainty crosses the second threshold, the coefficient again rises to 1.38. In Model (3), when uncertainty is below the first threshold (0.0553), governance level readiness does have marginally significant negative association with renewable energy innovation, but the impact becomes significantly negative and stronger when the threshold reaches the second (0.0553 to 0.1723) and third stage (above 0.1723) respectively. In Model (4), it is evident that uncertainty in relation to social readiness of emerging countries creates a significant positive impact on renewable energy innovation. When uncertainty is below the threshold 0.0866, the coefficient estimate is 2.954, but when it crosses the threshold (above 0.086), the coefficient decreases to 2.679. Table 11 summarizes the panel threshold regression results for the post-Kyoto Protocol period.

Threshold effects of uncertainty with country-level overall readiness on renewable energy innovation are observed for both the full sample and advanced economies during the post-Kyoto Protocol period. For the full sample, the coefficient is 1.10 when uncertainty falls below the threshold (0.1682) but decreases to 0.88 above this threshold, though the latter coefficient is statistically insignificant. Advanced economies exhibit similar patterns with a dual-threshold structure. When uncertainty is below the first threshold (0.084), the coefficient is 1.11. The coefficient decreases to 0.94 between the first and second thresholds (0.084–0.287) but increases to 1.16 when uncertainty exceeds 0.287. Across both samples, the first lag of uncertainty negatively influences renewable energy innovation, while GDP per capita demonstrates a positive and statistically significant effect.

5. Discussion and future policy implications

This section provides a critical analysis of the empirical findings and their policy implications. The results regarding the uncertainty threshold effect indicate that overall country-readiness and its key components—economic, governance, and social readiness—plays a significant role in driving renewable energy innovation across different uncertainty regimes. This impact is not static; rather, it varies depending on the stage of uncertainty. Policymakers must be attuned to the structural changes induced by uncertainty and implement necessary reforms in the readiness of a country to ensure sustained innovation in renewable energy, thereby supporting the transition to a green economy.

Our study shows that overall readiness of a nation significantly boosts renewable energy innovation amidst uncertainty, with a stronger impact in advanced economies compared to emerging ones. However, the positive contribution of country-level overall readiness to renewable innovation diminishes as uncertainty rises from low to high levels, a trend observed in both advanced and emerging economies. This finding aligns with our hypotheses, suggesting that severe uncertainty can destabilize the macro-structural conditions underpinning a country, with greater impacts on developing nations. ND-GAIN [18] state that countries with high readiness during periods of high vulnerability are better positioned to adopt innovative adaptive solutions that align with our results. Renewable energy requires favorable conditions for development with deliberate and coordinated efforts between government and business [64]. So, policymakers should adopt a holistic approach that integrates overall country-level readiness (economic, governance, social) into national energy policies, enabling effective green energy transitions through innovation, even amid high uncertainty.

Specifically, among the key structural components of a country's overall readiness, economic readiness—reflected in the World Bank's Ease of Doing Business index— positively influences renewable energy innovation during different stages of uncertainty with lesser impact on high uncertainty stage, true for both advanced and emerging economies. Doing Business indicators harness stakeholder pressures to drive structural reforms, address uncertainty [65] and enhance competitiveness through innovation rather than relying on inheritance [66]. Economic readiness refers to the ease of doing business, fostering a competitive environment that drives innovation and growth. Policymakers should prioritize building economic readiness by reforming trade and business regulations to ensure sustained economic growth through technological innovation in the long term [67]. In contrast, governance readiness negatively impacts renewable energy innovation across varying uncertainty regimes. While this effect is not statistically significant in advanced economies, it is significant in emerging economies. This finding contradicts with our hypothesis but aligns with existing literature, which highlights a 'mismatch' between existing country-level governance systems and biophysical systems, such as renewable

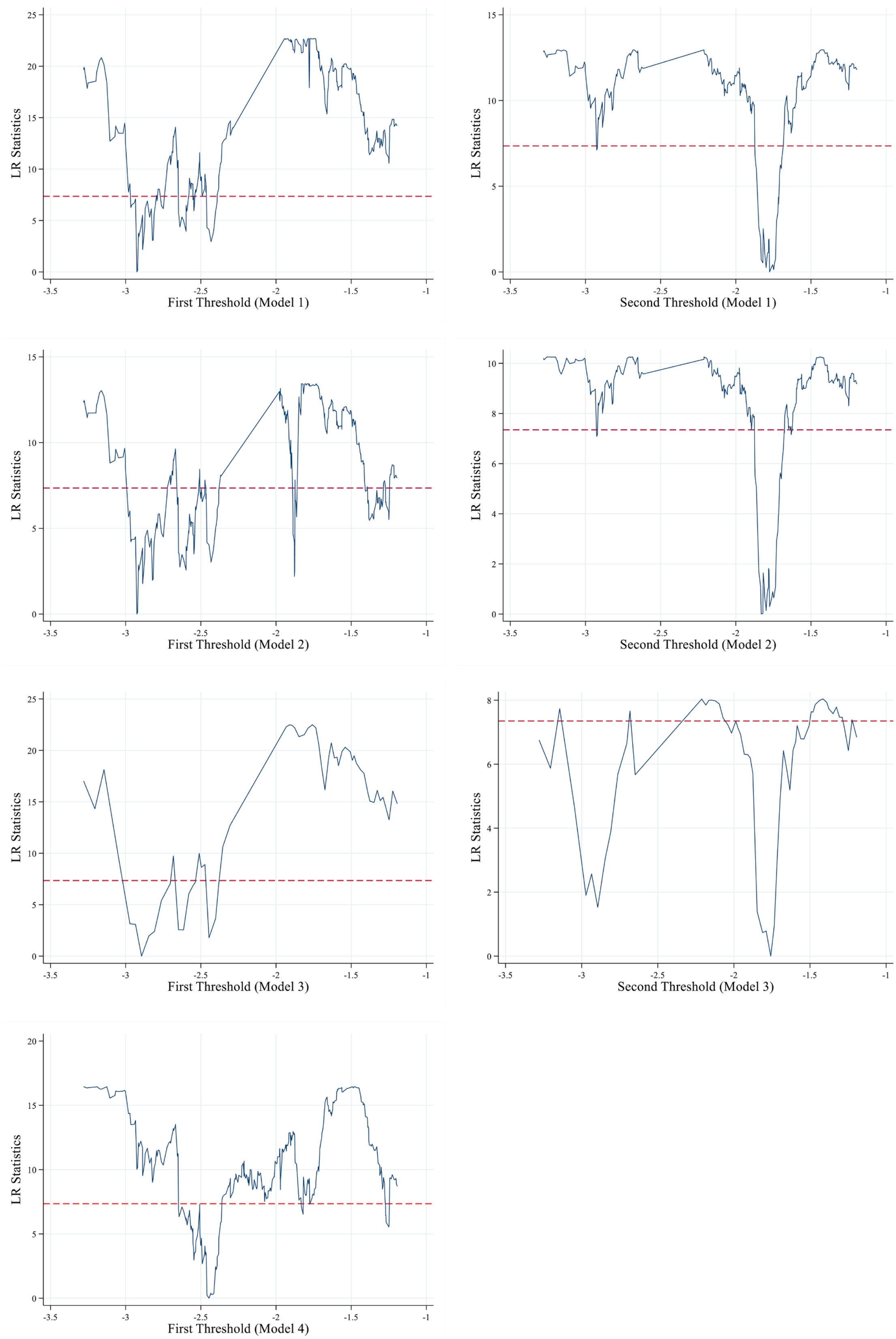

Fig. 7. LR diagrams with estimated threshold values (emerging economies).

Table 7
Threshold effect test results (post-Kyoto Protocol period).

Threshold models	No. of Thresholds	F value	P value	Critical Value			Threshold value	95 % confidence interval
				1 %	5 %	10 %		
Whole Sample	Single	11.42*	0.066	18.377	12.951	10.071	−1.7826	−1.8565,−1.7824
	Double	6.56	0.206	15.185	10.208	8.1463	−1.7826	−1.8458, −1.7824
Advanced Economy	Single	5.21	0.483	16.678	12.279	10.560	−2.4742	−2.5068,−2.4491
	Double	7.92*	0.066	13.789	9.5356	7.8123	−2.4742	−2.5851, −2.4491
							−1.2465	−1.5461,−1.2223

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

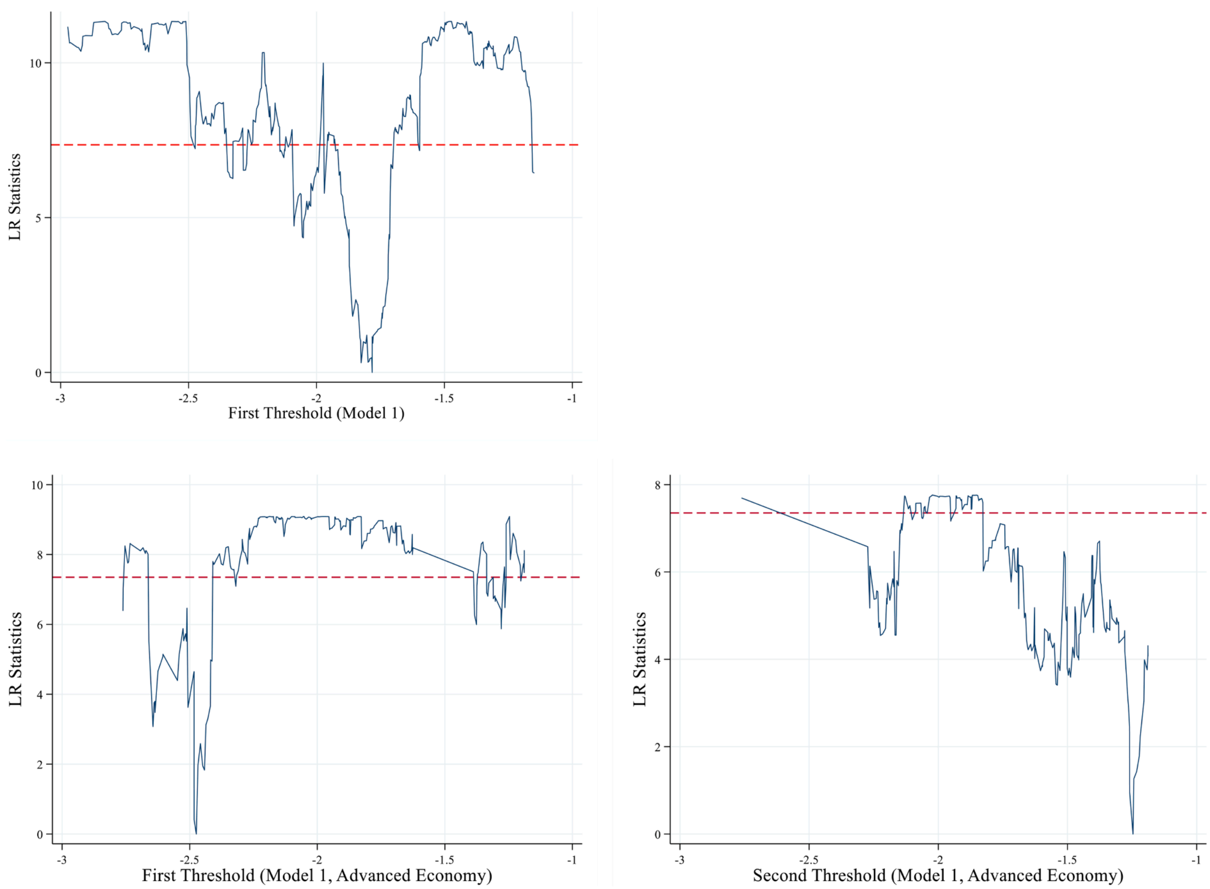

Fig. 8. LR diagrams with estimated threshold values (post-Kyoto Protocol period).

energy. To address this misalignment, new governance and management frameworks are required [68]. Furthermore, developing economies, often reliant on extractive institutions, may face additional barriers to innovation. For a sustainable future, countries should adopt forward-looking, adaptive, multi-actor governance models that foster long-term transformation, innovation and sustainability [69].

Country-level social readiness, as a critical structural component of a nation's overall readiness, demonstrates a significant positive association with renewable energy innovation across varying levels of uncertainty. Interestingly, this relationship is linear in advanced economies, where uncertainty does not impose a threshold effect. Conversely, in emerging economies, the association is non-linear, characterized by a significant double-threshold effect. The result validates our hypothesis and is supported by existing literature [37,70]. Social and political conditions can create diverse (positive, negative or a combination) impact on the growth and adoption of certain renewable energy technologies [71]. For greater adaptation and innovation of renewable energy, societal factors (education, ICT infrastructure etc.) should get as priority in energy policy as the technical ones.

Our findings indicate that uncertainty has a statistically significant negative association on renewable energy innovation, and the uncertainty similarly constrains the optimization of VPPs [72]. Nonetheless, through optimal scheduling within VPP systems, it is possible to maximize net profit for the stakeholders while minimizing real time emissions [73]. However, the successful implementation of VPPs is contingent upon four critical domains: (i) the legal system-supporting policies, prosumer policies, CO_2 limitation policies; (ii) the technical system-RES technologies, ESS technologies, virtual power plant control center, information and communication technology; (iii) the economic system-liberalization of energy sector, regionalization, local energy market, economic cost, demand side management; and (iv) the social system-changing behavior of energy end-users, ecological awareness, the necessity for energy security [74]. These implementation criteria closely align with the key dimensions of country-level readiness for climate adaptation, reinforcing the importance of readiness for successful renewable energy transition even under uncertainty.

Table 8
Results of threshold regression estimations (full sample).

Regressors	Model 1 $lnRN_{it-1}$	Model 2 $lnERN_{it-1}$	Model 3 $lnGRN_{it-1}$	Model 4 $lnSRN_{it-1}$
$lnUT_{it}$	0.042(0.384)	0.056 (0.292)	0.054(0.272)	0.0164 (0.703)
$lnUT_{it-1}$	−0.295*** (0.002)	−0.214** (0.003)	−0.186*** (0.009)	−0.101 (0.220)
$lnCE_{it}$	0.250(0.577)	0.340 (0.474)	0.4339 (0.203)	0.230 (0.397)
$lnGDP_{it}$	2.063*** (0.000)	2.363*** (0.000)	2.617*** (0.000)	0.925*** (0.001)
$lnTRO_{it}$	0.461(0.102)	0.503* (0.071)	0.482* (0.049)	0.3313 (0.18)
Threshold variable				
$lnUT_{it-1} < \theta_1)$	2.443** (0.018)	0.893** (0.015)	−1.829** (0.012)	2.894*** (0.000)
$\theta_1 \leq lnUT_{it-1} \leq \theta_2)$	2.017* (0.056)	0.654* (0.066)	−2.485*** (0.000)	2.681*** (0.000)
$lnUT_{it-1} > \theta_2$	1.645(0.102)	0.362 (0.303)	−1.610** (0.029)	2.467*** (0.000)
cons	−15.20*** (0.001)	−19.10*** (0.00)	−23.43*** (0.00)	−2.163 (0.462)

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; clustered robust standard error in parentheses.

Table 9
Results of threshold regression estimations (advanced economies).

Regressors	Model 1 $lnRN_{it-1}$	Model 2 $lnERN_{it-1}$	Model 3 $lnGRN_{it-1}$
$lnUT_{it}$	−0.006(0.743)	−0.0002(0.988)	−0.0027(0.886)
$lnUT_{it-1}$	−0.089** (0.024)	−0.0947*** (0.002)	−0.0532(0.101)
$lnCE_{it}$	0.332(0.205)	0.2210(0.480)	0.1769(0.458)
$lnGDP_{it}$	1.005***(0.003)	1.579***(0.000)	2.029***(0.000)
$lnTRO_{it}$	0.752***(0.000)	0.977***(0.000)	0.947**(0.005)
Threshold variable			
$lnUT_{it-1} < \theta_1)$	3.172***(0.001)	.841**(0.022)	−1.925(0.111)
$\theta_1 \leq lnUT_{it-1} \leq \theta_2)$	2.814***(0.002)	.534*(0.072)	−0.889(0.452)
$lnUT_{it-1} > \theta_2$	4.051***(0.000)	1.380*(0.056)	−1.976*(0.093)
cons	−3.208(0.378)	−10.07***(0.007)	−15.62*** (0.001)

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; clustered robust standard error in parentheses.

Table 10
Results of threshold regression estimations (emerging economies).

Regressors	Model 1 $lnRN_{it-1}$	Model 2 $lnERN_{it-1}$	Model 3 $lnGRN_{it-1}$	Model 4 $lnSRN_{it-1}$
$lnUT_{it}$	0.055(0.477)	0.077 (0.345)	0.065(0.393)	0.029 (0.671)
$lnUT_{it-1}$	−0.480*** (0.003)	−0.246** (0.014)	−0.399*** (0.008)	−0.013 (0.884)
$lnCE_{it}$	−0.064 (0.932)	0.257 (0.753)	.496(0.492)	−0.240 (0.646)
$lnGDP_{it}$	2.461*** (0.000)	2.55*** (0.000)	2.669*** (0.000)	1.126** (0.014)
$lnTRO_{it}$	0.436(0.238)	0.444 (0.22)	0.377(0.215)	0.4044 (0.203)
Threshold variable				
$lnUT_{it-1} < \theta_1)$	2.569** (0.039)	.963** (0.033)	−1.516* (0.077)	2.954*** (0.000)
$\theta_1 \leq lnUT_{it-1} \leq \theta_2)$	1.939(0.120)	.355(0.377)	−2.137*** (0.006)	2.679*** (0.000)
$lnUT_{it-1} > \theta_2$	1.470(0.212)	1.383* (0.051)	−2.627*** (0.000)	2.998*** (0.000)
cons	−19.04*** (0.00)	−20.90** (0.00)	−24.96*** (0.000)	−3.1891 (0.439)

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; clustered robust standard error in parentheses.

Table 11
Results of threshold regression estimations (post Kyoto Protocol).

Regressors	Model 1 $lnRN_{it-1}$	Model 2 $lnRN_{it-1}$
$lnUT_{it}$	0.0381(0.295)	0.0039(0.854)
$lnUT_{it-1}$	−0.0537(0.239)	−0.0432**(0.027)
$lnCE_{it}$	−0.0211(0.939)	−0.0135(0.895)
$lnGDP_{it}$	1.388***(0.001)	0.83888***(0.005)
$lnTRO_{it}$	−0.3049(0.215)	0.148511(0.389)
Threshold variable		
$lnUT_{it-1} < \theta)$	1.106*(0.061)	
$lnUT_{it-1} \geq \theta)$	.881(0.107)	
$lnUT_{it-1} < \theta_1)$		1.116**(0.036)
$\theta_1 \leq lnUT_{it-1} \leq \theta_2)$		.944*(0.070)
$lnUT_{it-1} > \theta_2$		1.162**(0.036)
cons	−8.112**(0.040)	−1.5570(0.608)

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; clustered robust standard error in parentheses.

6. Conclusion

Our study conducts a panel threshold econometric model that captures the non-linear relationship in the triadic interplay among renewable energy innovation, country-level readiness and uncertainty. The results show that uncertainty interacts with country-level overall readiness and its individual components-economic readiness, governance readiness and social readiness-to create distinct threshold effects on renewable energy innovation. Each dimension of readiness exhibits unique non-linear dynamics in response to varying levels of uncertainty, shaping the degree and nature of their influence on renewable energy innovation outcomes.

The dynamic interplay between uncertainty and readiness on renewable energy innovation serves as a catalyst, testing a country's energy system to adapt, evolve, and reveal its resilience. Our findings reveal that the optimal interplay within this triadic framework emerges under low-uncertainty conditions, where country-level overall readiness, including its economic and social exerts its maximum influence on renewable energy innovation outcomes. Conversely, during periods of high uncertainty, the contribution of readiness diminishes, posing challenges to the stability and progress of innovation. To mitigate these adverse effects, policymakers should implement targeted incentives that bolster readiness and enhance the system's ability to withstand and adapt to high uncertainty. In a surprising note, we find that country-level governance readiness negatively influences renewable energy innovation, especially in emerging economies with significance. The effect is relatively low in the low uncertainty regime but gradually increases as uncertainty increases to the next level. This result shows fundamental problems with the governance system around the world in dealing with renewable energy and uncertainty. Overall, our research highlights the necessity of aligning readiness strategies with uncertainty regimes to sustain and accelerate the transition to resilient and innovative renewable energy systems, thereby contributing to Society 5.0.

However, this study is not without limitations. First, to maintain a balanced panel dataset, the sample size was restricted to 65 countries. Future research can benefit from the inclusion of more countries, particularly from lower-middle-income and low-income countries, where such information is currently limited. Second, while our approach provides valuable insights, future research could expand on this study by exploring how specific policy instruments, or a combination of them, impact renewable energy innovation under uncertainty, from both individual country and regional perspectives. Furthermore, the triadic relationship among innovation, uncertainty, and readiness can be done by employing time series models and dynamic threshold models.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to better readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take (s) full responsibility for the content of the publication.

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CRediT authorship contribution statement

Mohammad Rakib Uddin Bhuiyan: Writing – review & editing, Writing – original draft, Validation, Formal analysis, Conceptualization. **Anupam Dutta:** Writing – review & editing, Writing – original draft, Resources, Formal analysis. **Gazi Salah Uddin:** Writing – review & editing, Writing – original draft, Supervision, Resources, Formal analysis. **Ali Ahmed:** Writing – review & editing, Writing – original draft, Supervision, Resources, Conceptualization.

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.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.sftr.2025.101158.

Data availability

Data will be made available on request.

References

[1] K. Fukuda, Science, technology and innovation ecosystem transformation toward society 5.0, Int. J. Prod. Econ. 220 (2020) 107460, https://doi.org/10.1016/j.ijpe.2019.07.033.
[2] M. Shamsuddoha, M.A. Kashem, T. Nasir, A review of transportation 5.0: advancing sustainable mobility through intelligent technology and renewable energy, Future Transp. 5 (2025) 8, https://doi.org/10.3390/futuretransp5010008.
[3] R. Jayabal, Towards a carbon-free society: innovations in green energy for a sustainable future, Results Eng. 24 (2024) 103121, https://doi.org/10.1016/j.rineng.2024.103121.
[4] A. Álvarez-Herránz, D. Balsalobre, J.M. Cantos, M. Shahbaz, Energy innovations-GHG emissions nexus: fresh empirical evidence from OECD countries, Energy Policy 101 (2017) 90–100, https://doi.org/10.1016/j.enpol.2016.11.030.
[5] UNCTAD, Technology and Innovation Report 2023, 2023. Geneva, Switzerland.
[6] D. Chiffi, S. Moroni, L. Zanetti, Types of technological innovation in the face of uncertainty, Philos. Technol. 35 (2022) 94, https://doi.org/10.1007/s13347-022-00587-3.
[7] N. Bloom, Fluctuations in uncertainty, J. Econ. Perspect. 28 (2014) 153–176, https://doi.org/10.1257/jep.28.2.153.
[8] K.N. Rather, M.K. Mahalik, Do world uncertainty and income inequality moderate the efficacy of environmental innovation in driving global renewable energy generation? Int. J. Sustain. Dev. World Ecol. (2024) 1–14, https://doi.org/10.1080/13504509.2024.2346920.
[9] G.-F. Feng, M. Zheng, Economic policy uncertainty and renewable energy innovation: international evidence, Innov. Green Dev. 1 (2022), https://doi.org/10.1016/j.igd.2022.100010.
[10] A. Ascani, L. Bettarelli, L. Resmini, P.-A. Balland, Global networks, local specialisation and regional patterns of innovation, Res. Policy 49 (2020) 104031, https://doi.org/10.1016/j.respol.2020.104031.
[11] B. Lin, J. Zhu, Determinants of renewable energy technological innovation in China under CO2 emissions constraint, J. Env. Manage. 247 (2019) 662–671, https://doi.org/10.1016/j.jenvman.2019.06.121.
[12] H. Ahir, N. Bloom, D. Furceri, The World Uncertainty Index. NBER Working Paper (no.29763), 2022. Cambridge.
[13] Notre Dame Global Adaptation Initiative, ND-GAIN Country Index. University of Notre Dame. https://gain.nd.edu/our-work/country-index/download-data/, 2024 [accessed January 3, 2025].
[14] B.E. Hansen, Threshold effects in non-dynamic panels: estimation, testing, and inference, J. Econ. 93 (1999) 345–368, https://doi.org/10.1016/S0304-4076(99)00025-1.
[15] R. Ishak, M. Mansor, The relationship between knowledge management and organizational learning with academic staff readiness for education 4.0, Eurasian J. Educ. Res. 20 (2020) 169–184, https://doi.org/10.14689/ejer.2020.85.8.
[16] J.J. Lee, J. Meng, Digital competencies in communication management: a conceptual framework of readiness for Industry 4.0 for communication professionals in the workplace, J. Commun. Manag. 25 (2021) 417–436, https://doi.org/10.1108/JCOM-10-2020-0116.
[17] G. Nhamo, Green economy readiness in South Africa: a focus on the national sphere of government, Int. J. Afr. Renaiss. Stud. - Multi- Inter- Transdiscipl. 8 (2013) 115–142, https://doi.org/10.1080/18186874.2013.834628.
[18] Notre Dame Global Adaptation Initiative, ND-GAIN country index technical report. https://gain.nd.edu/assets/581554/nd_gain_countryindex_technicalreport_2024.pdf, 2024 [accessed 5 March 2025].
[19] REN21, Renewables 2021 Global Status Report, 2021. Paris.
[20] D. Rodima-Taylor, M.F. Olwig, N. Chhetri, Adaptation as innovation, innovation as adaptation: an institutional approach to climate change, Appl. Geogr. 33 (2012) 107–111, https://doi.org/10.1016/j.apgeog.2011.10.011.
[21] P. Sollie, On Uncertainty in Ethics and Technology, 2009, pp. 141–158, https://doi.org/10.1007/978-90-481-2229-5_10.
[22] L.H. Sendstad, M. Chronopoulos, Sequential investment in renewable energy technologies under policy uncertainty, Energy Policy 137 (2020) 111152, https://doi.org/10.1016/j.enpol.2019.111152.
[23] I.S.M. Meijer, M.P. Hekkert, J.F.M. Koppenjan, The influence of perceived uncertainty on entrepreneurial action in emerging renewable energy technology; biomass gasification projects in the Netherlands, Energy Policy 35 (2007) 5836–5854, https://doi.org/10.1016/j.enpol.2007.07.009.
[24] J. Samuwai, J. Hills, Assessing climate finance readiness in the Asia-Pacific Region, Sustainability 10 (2018) 1192, https://doi.org/10.3390/su10041192.
[25] G. Singh, K. Rai, M.Y. Sokona, D. Hawila, Renewables readiness assessment design to action, Int. Renew. Energy Agency (Abu Dhabi) (2013).
[26] A.M. Domlyn, V. Scott, M. Livet, A. Lamont, A. Watson, T. Kenworthy, et al., R = MC ^{2} readiness building process: a practical approach to support implementation in local, state, and national settings, J. Community Psychol. 49 (2021) 1228–1248, https://doi.org/10.1002/jcop.22531.
[27] D. Audretsch, M. Feldman, R&D spillover and the geography of innovation and production, Am. Econ. Rev. 86 (1996) 630–640.
[28] M. Suzuki, Identifying roles of international institutions in clean energy technology innovation and diffusion in the developing countries: matching barriers with roles of the institutions, J. Clean. Prod. 98 (2015) 229–240, https://doi.org/10.1016/j.jclepro.2014.08.070.
[29] S. Thorne, Towards a framework of clean energy technology receptivity, Energy Policy 36 (2008) 2831–2838, https://doi.org/10.1016/j.enpol.2008.02.031.
[30] J. Grafström, P. Söderholm, E. Gawel, P. Lehmann, S. Strunz, Government support to renewable energy R&D: drivers and strategic interactions among EU Member States, Econ. Innov. New Technol. 32 (2023) 1–24, https://doi.org/10.1080/10438599.2020.1857499.
[31] H. Neofytou, A. Nikas, H. Doukas, Sustainable energy transition readiness: a multicriteria assessment index, Renew. Sustain. Energy Rev. 131 (2020) 109988, https://doi.org/10.1016/j.rser.2020.109988.
[32] Mondal MdAH, D. Hawila, S. Kennedy, T. Mezher, The GCC countries RE-readiness: strengths and gaps for development of renewable energy technologies, Renew. Sustain. Energy Rev. 54 (2016) 1114–1128, https://doi.org/10.1016/j.rser.2015.10.098.
[33] B. Lundvall, The Learning Economy and The Economics of Hope, ANTHEM Press, First. London, New York, 2016.
[34] C. Watanabe, K. Wakabayashi, T. Miyazawa, Industrial dynamism and the creation of a "virtuous cycle" between R&D, market growth and price reduction: the case of photovoltaic power generation (PV) development in Japan, Technovation 20 (2000) 299–312, https://doi.org/10.1016/S0166-4972(99)00146-7.
[35] X. He, J. Lin, J. Xu, J. Huang, N. Wu, Y. Zhang, et al., Long-term planning of wind and solar power considering the technology readiness level under China's decarbonization strategy, Appl. Energy 348 (2023) 121517, https://doi.org/10.1016/j.apenergy.2023.121517.

[36] P. Bayer, L. Dolan, J. Urpelainen, Global patterns of renewable energy innovation, 1990–2009, Energy Sustain. Dev. 17 (2013) 288–295, https://doi.org/10.1016/j.esd.2013.02.003.
[37] S. Yun, J. Lee, Advancing societal readiness toward renewable energy system adoption with a socio-technical perspective, Technol. Forecast. Soc. Change 95 (2015) 170–181, https://doi.org/10.1016/j.techfore.2015.01.016.
[38] P.H. Grünewald, T.T. Cockerill, M. Contestabile, P.J.G. Pearson, The socio-technical transition of distributed electricity storage into future networks—System value and stakeholder views, Energy Policy 50 (2012) 449–457, https://doi.org/10.1016/j.enpol.2012.07.041.
[39] J. Ye, L. Yan, X. Liu, F. Wei, Economic feasibility and policy incentive analysis of carbon capture, utilization, and storage (CCUS) in coal-fired power plants based on system dynamics, Environ. Sci. Pollut. Res. 30 (2022), https://doi.org/10.1007/s11356-022-24888-4.
[40] F. Egli, Renewable energy investment risk: an investigation of changes over time and the underlying drivers, Energy Policy 140 (2020), https://doi.org/10.1016/j.enpol.2020.111428.
[41] U. Korkut Pata, Does energy policy uncertainty matter for renewable energy and energy efficiency technologies? An affordable and clean energy perspective, Geosci. Front. 15 (2024) 101932, https://doi.org/10.1016/j.gsf.2024.101932.
[42] L. Bettarelli, D. Furceri, P. Pizzuto, N. Shakoor, Uncertainty and innovation in renewable energy, J. Int. Money. Finance 149 (2024) 103202, https://doi.org/10.1016/j.jimonfin.2024.103202.
[43] C.-W. Su, K. Khan, M. Umar, T. Chang, Renewable energy in prism of technological innovation and economic uncertainty, Renew. Energy 189 (2022) 467–478, https://doi.org/10.1016/j.renene.2022.02.110.
[44] T.H.A. Yuen, W.K.T. Yuen, Public investment on renewable energy R&D Projects: the role of geopolitical risk, and economic and political uncertainties, Energy Econ. 138 (2024) 107837, https://doi.org/10.1016/j.eneco.2024.107837.
[45] H. Tiismus, V. Maask, V. Astapov, T. Korõtko, A. Rosin, State-of-the-art review of emerging trends in renewable energy generation technologies, IEEe Access 13 (2025) 10820–10843, https://doi.org/10.1109/ACCESS.2025.3528640.
[46] A.K. Pandey, V.K. Jadoun, J.N. Sabhahit, Scheduling and assessment of multi-area virtual power plant including flexible resources using swarm intelligence technique, Electr. Power Syst. Res. 238 (2025) 111139, https://doi.org/10.1016/j.epsr.2024.111139.
[47] Pandey A.K., Jadoun V.K. S. Jayalakshmi N. Exploring the potential and avenues of renewable integrated energy resources through virtual power plant, 2025, p. 231–44. https://doi.org/10.1007/978-981-97-8464-6_20.
[48] A.K. Pandey, V.K. Jadoun, J.N. Sabhahit, S. Sharma, Interconnected operation and economic feasibility-based sustainable planning of virtual power plant in multi-area context, Smart Cities 8 (2025) 37, https://doi.org/10.3390/smartcities8010037.
[49] H. Wei, X. Kao, W. Wang, Quantitative research on China's virtual power plant policies: effectiveness evaluation and frontier trends, J. Clean. Prod. 461 (2024) 142684, https://doi.org/10.1016/j.jclepro.2024.142684.
[50] Y. Jin, W.T. Coombs, Y. Wang, T.G.L.A. van der Meer, B.N. Shivers, READINESS": a keystone concept beyond organizational crisis preparedness and resilience, J. Contingencies Crisis Manag. 32 (2024), https://doi.org/10.1111/1468-5973.12546.
[51] A. Atalay Mazlum, Strategic readiness as one of the ways to cope with uncertainty during the pandemic of COVID 19, E-Int. J. Educ. Res. (2022), https://doi.org/10.19160/e-ijer.1092163.
[52] L. Bottazzi, G. Peri, The international dynamics of R&D and innovation in the long run and in the short run, Econ. J. 117 (2007) 486–511, https://doi.org/10.1111/j.1468-0297.2007.02027.x.
[53] S. Jacobsson, A. Johnson, The diffusion of renewable energy technology: an analytical framework and key issues for research, Energy Policy 28 (2000) 625–640, https://doi.org/10.1016/S0301-4215(00)00041-0.
[54] J. Yi, S. Dai, L. Li, J. Cheng, How does digital economy development affect renewable energy innovation? Renew. Sustain. Energy Rev. 192 (2024) 114221 https://doi.org/10.1016/j.rser.2023.114221.
[55] J.-Z. Wang, G.-F. Feng, C.-P. Chang, How does political instability affect renewable energy innovation? Renew. Energy 230 (2024) 120800 https://doi.org/10.1016/j.renene.2024.120800.
[56] K.S. Herman, J. Xiang, Channeled through trade: how foreign environmental regulations induce domestic renewable energy innovation, Energy Res. Soc. Sci. 89 (2022) 102629, https://doi.org/10.1016/j.erss.2022.102629.
[57] B. Lin, J. Zhu, Determinants of renewable energy technological innovation in China under CO2 emissions constraint, J. Env. Manage. 247 (2019) 662–671, https://doi.org/10.1016/j.jenvman.2019.06.121.
[58] J. Huang, Q. Liu, X. Cai, Y. Hao, H. Lei, The effect of technological factors on China's carbon intensity: new evidence from a panel threshold model, Energy Policy 115 (2018) 32–42, https://doi.org/10.1016/j.enpol.2017.12.008.
[59] M. Su, Q. Wang, R. Li, L. Wang, Per capita renewable energy consumption in 116 countries: the effects of urbanization, industrialization, GDP, aging, and trade openness, Energy 254 (2022) 124289, https://doi.org/10.1016/j.energy.2022.124289.
[60] Q. Wang, Fixed-effect panel threshold model using Stata, Stata J.: Promot. Commun. Stat. Stata 15 (2015) 121–134, https://doi.org/10.1177/1536867X1501500108.
[61] R.M. West, Best practice in statistics: the use of log transformation, Ann. Clin. Biochem.: Int. J. Lab. Med. 59 (2022) 162–165, https://doi.org/10.1177/00045632211050531.
[62] D. Hoechle, Robust standard errors for panel regressions with cross-sectional dependence, Stata J.: Promot. Commun. Stat. Stata 7 (2007) 281–312, https://doi.org/10.1177/1536867X0700700301.
[63] International Monetary Fund, World Economic Outlook: A Rocky Recovery, 2023. Washington D.C.
[64] E. Smirnova, S. Kot, E. Kolpak, V. Shestak, Governmental support and renewable energy production: a cross-country review, Energy 230 (2021) 120903, https://doi.org/10.1016/j.energy.2021.120903.
[65] L.J. Ogbonna, F.C. Lawal, S.O. Okafor, Ease of doing business and entrepreneurial growth in the face of global economic policy uncertainty, Arch. Curr. Res. Int. 24 (2024) 336–348, https://doi.org/10.9734/acri/2024/v24i10936.
[66] K. Belayachi, J. Haidar, Competitiveness from innovation, not inheritance. Celebrating Reform 2008: Doing Business Case Studies, World Bank, Washington, D.C, 2008, pp. 16–21.
[67] J.B. Ang, Innovation and financial liberalization, J. Bank. Financ. 47 (2014) 214–229, https://doi.org/10.1016/j.jbankfin.2014.07.007.
[68] V. Galaz, F. Biermann, C. Folke, M. Nilsson, P. Olsson, Global environmental governance and planetary boundaries: an introduction, Ecol. Econ. 81 (2012) 1–3, https://doi.org/10.1016/j.ecolecon.2012.02.023.
[69] R. Kemp, D. Loorbach, Transition Management: A Reflexive Governance Approach. Reflexive Governance For Sustainable Development, Edward Elgar Publishing, 2006, https://doi.org/10.4337/9781847200266.00015.
[70] R. Bellamy, Social readiness of adaptation technologies, WIREs Clim. Change 10 (2019), https://doi.org/10.1002/wcc.623.
[71] N.J. Sheikh, D.F. Kocaoglu, L. Lutzenhiser, Social and political impacts of renewable energy: literature review, Technol. Forecast. Soc. Change 108 (2016) 102–110, https://doi.org/10.1016/j.techfore.2016.04.022.
[72] S. Yu, F. Fang, Y. Liu, J. Liu, Uncertainties of virtual power plant: problems and countermeasures, Appl. Energy 239 (2019) 454–470, https://doi.org/10.1016/j.apenergy.2019.01.224.
[73] A.K. Pandey, V.K. Jadoun, S.J. N, M. Singh, Decentralization of renewable energy sources based optimum scheduling and management through a virtual power plant, Env. Res. Commun. 6 (2024) 115021, https://doi.org/10.1088/2515-7620/ad9087.
[74] A. Setiawan, F.H. Jufri, F. Dzulfiqar, M.G. Samual, Z. Arifin, F.F. Angkasa, et al., Opportunity assessment of virtual power plant implementation for sustainable renewable energy development in Indonesia power system network, Sustainability 16 (2024) 1721, https://doi.org/10.3390/su16051721.