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# Convergence in renewable energy innovation and factors influencing convergence club formation

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ABSTRACT

Innovation and adaptation of renewable energy technologies significantly reduce carbon dioxide (CO2) emissions and increase energy efficiency. Understanding the convergence patterns in renewable energy innovation will enable policymakers to design policies to increase energy efficiency and renewable energy consumption and reduce CO2 emissions. This paper applies the convergence algorithm proposed by Philips and Sul to assess the convergence in renewable energy innovation for 90 countries covering the period between 1993 and 2018. This paper also examines the determinants/factors driving the convergence clubs of the countries using Probit and Logit regression. The convergence analyses suggest that there is no global convergence in renewable energy innovation. Findings highlight two convergence clubs: i) a club comprising more innovative countries and ii) another club that includes less innovative countries. We find that countries with higher income per capita, CO2 emissions per capita, research and development (R&D) investment, better environmental regulations and stronger institutional settings are more likely to be part of the innovative club. Countries should increase their R&D investment and environmental regulations and improve their institutional quality to increase their likelihood of belonging to a more innovative club. Furthermore, less innovative countries could promote policies to transfer renewable energy technologies from innovative countries.

## 1. Introduction

Ever-increasing threads of climate change led many countries to pledge net zero emission targets or to decrease their greenhouse gas emissions to mitigate the negative implications of climate change [1]. United Nations Framework Convention on Climate Change (UNFCCC) established an international treaty in 2015, so-called the Paris agreement (see Ref. [2]), and countries agreed to reduce their emissions by nationally determined contributions [3]. One effective way of meeting emission reduction targets is to increase renewable energy consumption and promote green technological innovation.

It has been found that green innovation enhances energy efficiency (see e.g. Ref. [4]), deployment of renewable energy (see e.g. Ref. [5]) and reduces carbon emissions (see e.g., Ref. [6,7]). Therefore, understanding and analyzing the convergence in renewable energy innovation (REI) is essential to design policies to promote renewable energy consumption and reduce carbon emissions. In particular, global convergence in REI suggests that countries with lower levels of REI are gradually catching up with those with higher REI levels. Achieving global convergence in REI would suggest that countries invest in REI to promote renewable energy consumption and work towards better environmental outcomes. However, the existence of non-convergence in REI would suggest that some countries innovate more environmentally friendly technologies and others that fall behind in green innovation should implement policies to increase their green innovation and increase the transfer of such environmentally friendly technologies from more innovative countries. Furthermore, in the case of non-convergence in REI, it would be essential to examine the factors explaining the formation of different REI clubs to identify factors that countries could alter to achieve higher REI and belong to more innovative clubs.

Even though the existing studies examined convergence in various environmental factors (see e.g., Ref. [8–15]), convergence in REI has been under-investigated. Therefore, this paper contributes to the existing empirical literature in various ways. Firstly, cross-country convergence in REI has not been examined and this paper contributes to the existing literature by examining the convergence in REI for 90 countries covering the 1993–2018 period (see e.g. Ref. [16], for energy innovation convergence across Chinese provinces). Secondly, unlike other literature which employed other methods of convergence (see e.g., Ref. [9,17,18]), this paper uses the convergence test proposed by Phillips and Sul

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[19,20]. The main advantage of the latter convergence method is that it allows heterogeneous convergence paths across countries and identifies convergence clubs among different countries. Thirdly, based on the convergence in REI analysis, Probit and Logit models will be used to examine the factors that affect the probability/likelihood of a country being part of a particular convergence club (i.e., a more innovative club). Given that REI is key in increasing renewable energy consumption and energy efficiency and decreasing carbon emissions, it is essential to understand the factors that affect the likelihood of a country belonging to a more innovative club.

The findings of this study demonstrate that there is no global convergence in REI for 90 countries and that there are two convergence clubs: i) a club that consists of countries with high levels of REI and ii) another club with low levels of REI. Probit and logit models also show that countries that are more developed, invest more in research and development (R&D), and have better institutions and environmental regulations are more likely to be in more innovative clubs.

The rest of the paper is organized as follows. Section 2 provides a

**Table 1**
Technological innovation, energy efficiency and environmental quality.

Panel A. Technological innovation and energy efficiency

| Study | Period | Spatial unit | Methods | Findings |
|---|---|---|---|---|
| Ajayi and Reiner [36] | 1995–2009 | 17 EU countries | Random and fixed effects | Patents reduces firm level energy intensity |
| Chen et al. [35] | 1990–2016 | 19 MENA countries | cross-sectional autoregressive distributed lag (CS-ARDL), cross-sectional distributed lag (CS-DL) and common correlated effect-based generalized method of moments (CCE-GMM) | Technological innovation has a positive impact on energy efficiency |
| Herrerias et al. [37] | 2006–2010 | 30 Chinese provinces | panel estimations accounting for the heteroscedasticity and the serial correlation | Indigenous and foreign innovations have an energy-reducing effect in this country |
| Hille and Lambernd [136] | 2002–2017 | South Korea | Limited Information Maximum Likelihood (LIML) | Innovation lowers energy intensity |
| Huang et al. [38] | 2000–2013 | 30 Chinese provinces | fixed effects (FE) and Driscoll and Kraay standard errors | Indigenous innovations reduce energy intensity |
| Liu et al. [34] | 1990–2019 | BRICS countries | Westerlund co-integration, method of moments quantile regression (MMQR), and panel causality | Technological innovation reduces energy intensity |
| Pan et al. [32] | 2006–2015 | 30 Chinese provinces | acyclic graph (DAG) and structure vector autoregrression (SVAR) | Technology innovation improves energy efficiency |
| Pan et al. [33] | 1976–2014 | Bangladesh | Structural vector autoregression (SVAR) | Technological innovation enhances energy intensity |
| Sun et al. [4] | 1990–2014 | 71 countries | Maximum likelihood | Green innovation reduces energy efficiency |
| Wang and Wang [30] | 2001–2013 | 284 Chinese cities | Generalized Method of Moment (GMM) | Technological innovation improves energy efficiency |
| Wurlod and Noailly [31] | 1975–2005 | 17 OECD countries | Cost function approach and iterative seemingly unrelated regression | Green patents reduce energy intensity |

Panel B. Technological innovation and environmental quality

| Study | Period | Spatial unit | Methods | Findings |
|---|---|---|---|---|
| Altıntaş and Kassouri [23] | 1985–2016 | 12 EU countries: Austria, Denmark, France, Germany, Italy, The Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK. | Linear and nonlinear panel ARDL estimations | Government energy technology research, development, and demonstration (RD&D) budget reduces carbon footprints |
| Chen and Lee [6] | 1996–2018 | 96 countries | Spatial Autoregression Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM) | Technological innovation reduces CO2 emissions |
| Chen and Lei [24] | 1980–2014 | 30 countries | Panel quantile regression | Technology innovation reduces CO2 emissions |
| Destek and Manga [28] | 1995–2016 | 10 big emerging markets (BEM) countries: Argentina, Brazil, China, India, Indonesia, Mexico, Poland, South Africa, South Korea, and Turkey | Stochastic Impacts by Regression on Population, Affluence and Technology (SIRPAT) model | Technological innovation reduces CO2 emissions, but does not affect ecological footprint |
| Erdoğan et al. [29] | 1971–2017 | 14 of the G20 countries | Common Correlated Effect (CCE) & Augmented Mean Group (AMG) estimator | No significant effect on the energy sector, transport sector, and other sectors, but innovation reduces co2 emissions in the industrial sector |
| Hashmi and Alam [21] | 1999–2014 | OECD countries | Fixed-effects, random-effects and Generalized Method of Moments (GMM) | Innovation reduces CO2 emissions |
| Khan et al. [22] | 1995–2019 | 19 countries of the European Union (EU) | Fully Modified Ordinary Least Squares (FMOLS), the Dynamic Ordinary Least Squares (DOLS) and the Fixed Effects Ordinary Least Squares OLS (FE-OLS) | Technological innovation reduces CO2 emissions |
| Lin and Zhu [25] | 2000–2015 | 30 Chinese provinces | Fixed effects and random effects | Renewable energy technological innovation reduces CO2 emissions |
| Shahbaz et al. [7] | 1984–2018 | China | bootstrapping autoregressive distributed lag modeling (BARDL) | Technological innovations reduce carbon emissions |
| Shao et al. [27] | 1980–2018 | Next-11 (N11) countries: Bangladesh, Egypt, Indonesia, Iran, South Korea, Mexico, Nigeria, Pakistan, Philippines, Turkey, and Vietnam | cross-sectional augmented autoregressive distributed lags (CS-ARDL) | Green technology innovation shows a negative impact on CO2 emissions |
| Többelmann and Wendler [26] | 1992–2014 | EU-27 countries | GMM | Environmental innovation reduces Co2 |

literature review on the importance of environment-related technologies in reducing greenhouse gas emissions and improving energy efficiency. Furthermore, we provide a literature review on the convergence analysis in section 2. Section 3 offers the methodology and data, and the results are presented in Section 4. Section 4 provides the final convergence clubs in REI and then offers results with the probit/logit models to examine the factors that increase the likelihood/probability of belonging to a particular final convergence club. Finally, section 5 concludes and provides policy recommendations.

## 2. Literature review

### 2.1. Innovation, pollution and energy efficiency

Green and renewable energy innovation is considered to be an essential factor in promoting energy efficiency and reducing carbon emissions. Hence, many studies have examined the impact of green, renewable and environmental technologies on energy intensity and environmental quality. Table 1 summarizes the findings of these studies. Panel A of Table 1 provides the details of the literature review that examined the relationship between technological innovation and energy efficiency. On the other hand, Panel B of Table 1 offers the literature details that evaluated the impact of technological innovation on environmental quality.

Using panel data for the OECD countries between 1999 and 2014, Hashmi and Alam [21] demonstrated that environmentally friendly patents reduce carbon emissions. Examining the panel data of 19 European Union countries between 1995 and 2019, Khan et al. [22] showed that technological innovation reduces CO2 emissions in medium and high quantiles. Similarly, Altıntaş and Kassouri [23] showed that the government energy technology research, development, and demonstration (RD&D) budget reduces carbon footprints in 12 European Union (EU) countries. On the other hand, using a panel of 96 countries from 1996 to 2018, Chen and Lee [6] show that technological innovation reduced CO2 emissions in highly globalized countries. Using panel data from 30 countries during the 1980–2014 period, Chen and Lei [24] found that technological innovation reduces CO2 emissions. Similar results are found for China [7,25], EU countries [26], next-11 countries [27], 10 big emerging markets [28], and G20 countries [29].

Green innovation also reduced energy intensity and improved energy efficiency in most countries. Using a panel data set of 71 countries between 1990 and 2014, Sun et al. [4] demonstrated that green technologies improved energy efficiency. Wang and Wang [30] found that technological innovation reduced energy intensity in 284 Chinese cities between 2001 and 2013. Analyzing 14 sectors across 17 OECD countries between 1975 and 2005, Wurlod and Noailly [31] demonstrated that green patents reduced energy intensity across different sectors. Similarly, the existing studies found that the innovation increases energy efficiency in 30 Chinese provinces [32], Bangladesh [33], Brazil, Russia, India, China and South Africa (BRICS) countries [34], 19 Middle East and North African (MENA) countries [35] and in EU countries [36]. Finally, using firm-level data, Herrerias et al. [37] and Huang et al. [38] found that indigenous and foreign innovations lower energy intensity across Chinese provinces.

Overall, the existing literature found that green and renewable energy innovation is vital in achieving energy efficiency and reducing carbon emissions for a different set of countries. Therefore, it is essential to examine the convergence in green and renewable energy innovation for countries to design policy agendas for promoting REI and renewable energy consumption.

### 2.2. Convergence analysis

The convergence analysis has long been implemented to examine the convergence in living standards across countries. There has been an extensive number of studies that examined the income convergence across countries (see e.g., Ref. [39–43]) and regions (see e.g., Ref. [44–48]) based on the classical theories of the convergence (see e.g., Ref. [49–51]). However, due to the increased importance of mitigating the negative implications of climate change and global warming, the recent literature has extensively examined the convergence of environmental factors. Table 2 summarizes the literature that assessed convergence in environmental factors such as carbon dioxide (CO2) emissions, ecological footprint, different types of energy consumption and energy intensity (efficiency), and renewable energy consumption.

One stream of literature examined the convergence in CO2 emissions using a different set of countries, periods, and dependent variables. Most of the analyses employed the log *t*-test of Phillips and Sul [19,20] to examine convergence in CO2 emissions and found various convergence clubs but not a global convergence (see e.g., Ref. [8,14,52–56]). However, some studies also identified global and conditional convergence in CO2 emissions. For instance, Gao et al. [57] examined convergence in energy-related CO2 emissions across Chinese provinces between 1995 and 2017 and found global convergence. On the other hand, Marrero et al. [58] carried out the beta and sigma convergence analysis, and Phillips and Sul [19,20] log *t*-test to examine the CO2 emissions per capita from road transport and identified conditional convergence based on economic conditions and fuel prices, and no convergence clubs were found. Furthermore, Parker and Bhatti [59] pointed out the importance of structural breaks in identifying convergence behavior. Their paper found a global convergence in CO2 emissions per capita between 1971 and 2017 across 17 Asian countries. However, when they examined the sample before and after the 1997 East Asian crises, they identified different convergence clubs rather than a global convergence. Finally, Zheng and Yuan [60] examined the convergence in CO2 emissions from different sectors across Chinese provinces between 1997 and 2018 and identified an absolute, conditional and diverse set of convergence clubs based on CO2 emissions generated by various sectors.

Another stream of literature used a different environmental quality proxy (i.e., ecological footprint) rather than CO2 emissions to examine the environmental quality (degradation) convergence across countries. Erdogan and Okumus [61] used panel data covering 89 countries between 1961 and 2016 and found no global convergence in ecological footprint, and convergence clubs were identified for different income groups. On the other hand, convergence in different geographical clusters is analyzed by other research papers. Işık et al. [62], Tillaguango et al. [63] and Ulucak et al. [13] examined convergence in ecological footprint across countries in North America (i.e., Canada, Mexico, United States), Latin America and Sub-Saharan African countries, respectively. While Işık et al. [62] demonstrated that there is a convergence in the ecological footprint across Canada, Mexico and the United States, Tillaguango et al. [63] and Ulucak et al. [13] found no absolute convergence in the ecological footprint across Latin American and Sub-Saharan countries, respectively, and identified different convergence clubs.

Convergence in energy intensity across different countries and regions within countries has also been widely examined. For example, convergence in energy intensity between Chinese cities (e.g., Ref. [64,65]) and provinces [66] were examined, and neither of the papers [64–66] found global convergence across Chinese regions and identified a different set of convergence clubs, and suggested that China should adopt region-specific policies to increase the energy efficiency. Similarly, Dehghan Shabani and Shahnazi [18] and Taştan and Yıldız [67] also assessed energy intensity variation across Iranian and electricity consumption across Turkish provinces, respectively, and found no global convergence in energy consumption in each respective analysis but identified convergence clubs. Even though most of the existing studies also found no global convergence in energy intensity across a set of countries and identified different convergence clubs (see e.g., Ref. [10,11,68]), a handful number of studies found convergence in energy intensity across a specific set of countries (e.g. Ref. [17]). In general, the convergence analysis in energy intensity revealed different

**Table 2**
Convergence analysis.

| Study | Period | Sample | Method used | Variables |
|---|---|---|---|---|
| Panel A. Convergence in CO2 emissions | | | | |
| Belloc and Molina [8] | 1970–2018 | 19 Latin American countries | Phillips and Sul [19,20] log *t*-test | Greenhouse gas emissions per capita and per GDP |
| Bhattacharya et al. [52] | 1990–2014 | 70 countries | Phillips and Sul [19,20] log *t*-test | Carbon emissions intensity |
| Cialani and Mortazavi [53] | 1970–2018 | 28 EU countries | Phillips and Sul [19,20] log *t*-test | Aggregate CO2 emissions per capita emissions of fossil CO2 |
| Dogah and Churchill [54] | 1960–2018 | Seven ASEAN member states: Indonesia, Vietnam, Malaysia, Singapore, Brunei Darussalam, Philippines and Thailand | Phillips and Sul [19,20] log *t*-test | Aggregate Co2 emissions, and Co2 emissions per capita emerging from coal, oil, natural gas and cement production. |
| Gao et al. [57] | 1995–2017 | Chinese provinces | Phillips and Sul [19,20] log *t*-test | Energy-related CO2 emissions |
| Ivanovski and Churchill [55] | 1990–2017 | Australian regions | Phillips and Sul [19,20] log *t*-test | Greenhouse gas emissions |
| Marrero et al. [58] | 1990–2014 | 22 European countries | β-convergence, σ-convergence, and Phillips and Sul (2007 [20], log *t*-test | CO2 emissions per capita from road transport |
| Parker and Bhatti [59] | 1971–2017 | 17 Asian countries | Phillips and Sul [19,20] log *t*-test | Co2 emissions per capita |
| Tiwari et al. [56] | 1976–2014 | US states | Pesaran (2007) unit root test, Becker et al. [69] fourier stationarity test, Phillips and Sul [19,20] log *t*-test | CO2 emissions |
| Wojewodzki et al. [14] | 2000–2016 | 217 countries | The mobility Probability Plot (MPP) developed by Cheong and Wu (2018) | Relative carbon intensity and relative per capita carbon emissions |
| Zheng and Yuan [60] | 1997–2018 | 30 Chinese provinces | β-convergence & Phillips and Sul [19,20] log *t*-test | Co2 emission intensity |
| Panel B. Convergence in ecological footprint | | | | |
| Erdogan and Okumus [61] | 1961–2016 | 89 countries | Phillips and Sul [19,20] log *t*-test | Ecological footprint |
| Işık et al. [62] | 1961–2016 | USA, Canada, and Mexico | Threshold autoregressive (TAR) panel unit root test | Ecological footprint |
| Tillaguango et al. [63] | 1990–2016 | 16 Latin American countries | Phillips and Sul [19,20] log *t*-test | Ecological footprint |
| Ulucak et al. [13] | 1961–2014 | 23 Sub-Saharan Africa countries | Phillips and Sul [19,20] log *t*-test | Ecological footprint and its sub-components |
| Panel C. Convergence in energy intensity | | | | |
| Bangjun et al. [64] | 2005–2019 | 243 Chinese cities | Phillips and Sul [19,20] log *t*-test | Energy consumption per capita |
| Bello and Ch'ng [17] | 1988–2019 | 15 West African countries | σ convergence, β convergence, and stochastic convergence | Energy consumption/real GDP |
| Dehghan Shabani and Shahnazi [18] | 2002–2016 | Iranian provinces | σ convergence, β convergence, and stochastic convergence | Energy intensity |
| González-Álvarez et al. [10] | 1990–2015 | 109, 157 and 182 countries for different types of energy intensity | Phillips and Sul [19,20] log *t*-test | Non-renewable, non-clean and total energy intensity |
| He and Chen [66] | 1990–2017 | 30 Chinese provinces | Phillips and Sul [19,20] log *t*-test | Energy consumption per capita |
| Peng et al. [11] | 1996–2019 | 60 countries along the Belt and Road Initiative (BRI) route | Phillips and Sul [19,20] log *t*-test | Total-factor energy efficiency based on stochastic frontier approach combined with the distance function |
| Santiago et al. [68] | 1970–2014 | 21 Latin America and the Caribbean countries | Phillips and Sul [19,20] log *t*-test | Primary energy consumption/Real GDP |
| Taştan and Yıldız [67] | 2000–2020 | 81 Turkish cities | Phillips and Sul [19,20] log *t*-test | Total electricity consumption, and industrial and residential electricity consumption per capita |
| Zhu and Lin [65] | 2005–2016 | 193 Chinese cities | Phillips and Sul [19,20] log *t*-test | Total energy consumption/real GDP |
| Panel D. Convergence in renewable energy consumption | | | | |
| Berk et al. [69] | 1990–2014 | 14 EU countries | System Generalized Method of Moments (GMM) | Share of renewables in primary energy consumption |
| Bigerna et al. [9] | 1990–2018 | 176 countries | β- and σ-convergence | Renewable energy consumption (% of total final energy consumption) |
| Demir and Cergibozan [71] | 1971–2015 | 28 OECD countries | difference-GMM and system-GMM | Alternative and nuclear energy (% of total energy use) |
| Kasman and Kasman [70] | 1990–2018 | 15 core EU countries | β- and σ-convergence & Phillips and Sul [19,20] log *t*-test | Renewable energy consumption per capita |
| Qahtan et al. [137] | 1990–2016 | MENA net oil-exporting and importing countries | Stochastic convergence | Total energy consumption per capita, non-renewable energy consumption per capita, and renewable energy consumption per capita |
| Saba and Ngepah [12] | 2000–2018 | 183 countries in Sub-Saharan Africa (SSA), Middle East and North Africa (MENA), Europe and Central Asia (ECA), East and South Asia and the Pacific (ESAP) and America. | Phillips and Sul [19,20] log *t*-test | Renewable energy consumption (% of total fnal energy consumption) |
| Zhang et al. [15] | 2005–2014 | 20 Latin American countries | β- and σ-convergence | Total factor efficiency of renewable energy |

convergence clubs and recommended tailored policy recommendations based on the convergence clubs.

Finally, a number of studies examined the convergence patterns in renewable energy consumption, and most of the existing studies identified convergence in renewable energy consumption across a set of countries. For instance, convergence in renewable energy across EU countries (see e.g., Berk et al. [69] for 14 EU countries; Kasman and Kasman [70] for 15 core EU countries), 28 OECD countries [71] and the Middle East and North African (MENA) countries were identified. On the other hand, Bigerna et al. [9] employed large panel data covering 176 countries between 1990 and 2018 and found a sigma-absolute and conditional beta-convergence in renewable energy consumption for several groups of countries. Zhang et al. [15] demonstrated no σ-convergence and absolute β-convergence in the total factor efficiency growth of renewable energy in Latin America but identified a significant conditional convergence. Finally, using convergence analysis developed by Phillips and Sul [19,20], Saba and Ngepah [12] examined the convergence of renewable energy consumption between 183 countries in Sub-Saharan Africa (SSA), Middle East and North Africa (MENA), Europe and Central Asia (ECA), East and South Asia and the Pacific (ESAP) and America, and found convergence clubs in renewable energy across different regions.

To the best of our knowledge, even though the convergence in different environmental factors (e.g., Co2 emissions, ecological footprint, different types of energy consumption) has been extensively studied, only a few studies have examined the convergence in green and renewable energy innovation. For example, to our knowledge, only Bai et al. [16] examined the convergence in renewable energy technology innovation across 30 Chinese provinces and found that there were three distinctive convergence clubs, and increased research and development (R&D) investment and environmental regulation increased the likelihood of being part of the high innovation provinces.

This study aims to fill this gap by examining the convergence in green and renewable energy innovation for 90 countries between 1993 and 2018 and the factors that explain the probability/likelihood of belonging to a particular final convergence club.

## 3. Methods and data

### 3.1. Methodology

The beta and sigma convergence and convergence clubs are the most commonly used methods to examine the convergence of different socioeconomic factors. The sigma convergence measures whether the dispersion between the countries increases or decreases. On the other hand, beta convergence examines the catch-up concept (e.g., economic growth levels of less developed countries are relatively higher than those of rich countries, suggesting catch-up between countries). In general, beta convergence could be unconditional or conditional. The growth of a given variable is regressed on the initial levels of the dependent variable to test absolute convergence. On the other hand, conditional beta convergence analysis includes a set of explanatory variables to examine the conditional convergence of a given variable. Finally, club convergence occurs when different countries follow different linear models and reach different steady states when they are grouped based on their initial conditions [72]. The most commonly used test is the log *t*-test developed by Phillips and Sul [19,20], which examines global convergence and potential multiple steady states.

The traditional convergence models (e.g., Ref. [49–51]) assume a single steady state, and poor-performing countries grow faster than the better-performing countries. However, one of the problems of these traditional convergence models is that the coefficients are biased if transitional conditions are heterogeneous [20]. For instance, neoclassical convergence models assume that the technological progress across countries is homogeneous, yet it is not reasonable to assume such homogeneity, and more recent models started to consider cross-country heterogeneity (e.g., Ref. [73,74]). Similarly, innovation progress encompasses heterogeneity (e.g. Ref. [75]). Therefore, analyzing the green innovation convergence across countries requires accounting for heterogeneity across countries, and therefore, we apply the log *t*-test proposed by Phillips and Sul [19,20].

To test for the green and renewable energy innovation (GREI) convergence, we use the panel data variable $GREI_{it}$, and the panel variable is composed of two time-varying factors:

$$logGREI_{it} = \delta_{it}\mu_t \tag{1}$$

where $i = 1, 2, \ldots, N$ and $t = 1, 2, \ldots, T$. $i$ and $t$ represent countries and periods, respectively. Furthermore, $N$ and $T$ are the numbers of countries and years in the panel data, respectively. $logGREI_{it}$ is the natural logarithm of the GREI in a given country $i$ at time $t$.[1] $\delta_{it}$ is the idiosyncratic component and measures the idiosyncratic distance between the common factor $\mu_t$ and the systematic part of $GREI_{it}$. The null hypothesis of the model suggests that $\delta_{it}$ converges to $\delta$. To test cross-country dispersion, Phillips and Sul [19] develop a panel relative transition parameter, $h_{it}$, as follows:

$$h_{it} = \frac{log\ GREI_{it}}{\frac{1}{N}\sum_{i=1}^{N} log\ GREI_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum_{i=1}^{N}\delta_{it}} \tag{2}$$

which measures the loading coefficient $\delta_{it}$ in relation to the panel average at time $t$. In other words, equation (2) eliminates the common growth component by scaling and measures the transition element for country $i$ relative to the cross-section average and is therefore called the "relative" transition. Once equation (2) is applied, the cross-country dispersion is used:

$$H_t = \frac{1}{N}\sum_{i=1}^{i=N}(h_{it}-1)^2 \tag{3}$$

Under the null hypothesis of convergence, a panel relative transition parameter $h_{it}$ converges to unity and, therefore, the cross-country dispersion, $H_t$, convergences to zero. To test the hypothesis, the following log t regression is used:

$$log\frac{H_1}{H_t} - 2\log(\log(t)) = \alpha + \gamma \log t + u_t \text{for} t = [\tau T], [\tau T]+1, \ldots, \text{and} \tau T > 0 \tag{4}$$

where $u_t$ is the error term and $\tau$ represents the fraction of the sample that is discarded from the sample. It is recommended that 30 % of the sample be discarded when it consists of time periods less than 50 [19]. Based on this log t regression analysis, the following hypothesis is tested:

$H_0 : \delta_i = \delta$ and $\alpha \geq 0$.

$H_1 : \delta_i \neq \delta$ and $\alpha < 0$.

Based on the above algorithm, the steps for carrying out the analysis are provided in section 4.1 of Phillips and Sul [19], and Schnurbus et al. [76] offered additional adjustments to the original procedure. This procedure is also provided in detail by Du [77] to carry out the analysis using the Stata software. For interested readers, the technical component of the procedure is provided in Phillips and Sul [19,20] and Du [77], but the steps carried out are explained as follows.

Step 1: The countries in the panel are sorted based on their innovation levels in the last period.

Step 2: The core group is being sorted. The first group of countries is selected as a core convergence group if the test statistic obtained from the log t regression (Equation (4)) is greater than −1.65. The log t regression for the sub-groups is carried out to select an

[1] As some of the countries did not have any patent registered in certain years, the natural logarithm of GREI+1 is taken.

additional set of countries to include in the core group that results in the largest $t$-test statistic.
Step 3: Sieve countries for club membership. Countries are included in the club if the test statistic is greater than the critical value of $c^*$.
Step 4: Form a group of the remaining countries that are not sieved by step 3, and perform the log $t$-test for this group. If the test statistic is greater than $-1.65$, the subgroup forms another convergence club. Otherwise, steps 1, 2 and 3 are repeated.
Step 5: Club merging procedure is carried out to examine whether two subsequent initial clubs may be merged.

Before carrying out the analysis, we made various parameter choices. Based on the Monte Carlo experiments of Phillips and Sul [19], 30 % of the sample is discarded as our sample consists of time periods less than 50. Furthermore, the sieving criterion ($c^*$) is set to zero as the empirical analysis of this paper consists of a small-time series based on the recommendation of Phillips and Sul [19,20].

After obtaining the final convergence clubs, we will examine the factors that explain the probability/likelihood of belonging to a specific final convergence club by using the Probit and Logit models (see e.g. Ref. [10–12,64,65,78–82], among many others). We will either use standard Probit/Logit models or ordered versions of the models if 2 or more than 2 final convergence clubs exist, respectively.[2]

### 3.2. Data and variable selection

Environment-related patent data is widely used as a proxy for GREI (see e.g., Ref. [4,31,83,84]), and the data is obtained from the OECD [85]. We follow the procedure used by Wurlod and Noailly [31] to identify green and renewable energy patents. In particular, we used the triadic patent families as these patents are filed at the European, Japanese and US patent offices (EPO, JPO and USPTO, respectively) to protect the same invention. In other words, we only counted the patents that three patent offices protect as these technologies are expected to have a higher economic return. Furthermore, accounting for only these patents reduces the patent quality differences, and home advantage and the influence of geographical location are eliminated. As a final step, we use the resident address of the inventor to allocate the patents to countries and priory dates to allocate the patents to respective years. Based on these criteria, we ended up with annual data that covers the period between 1993 and 2018, and 90 countries were used for the analysis (see Appendix Table A1 for the list of countries).

We also collect a set of explanatory variables to examine the factors that affect the probability/likelihood of countries belonging to final convergence clubs. In particular, factors that are found to be important for innovation are R&D investment, development level, institutional quality, human capital, environmental regulation, renewable energy consumption share, energy intensity and CO2 emissions.

R&D investment is found to be one of the main drivers of innovation (see e.g., Ref. [86–88]), which is also a critical factor in promoting green innovation [16]. Furthermore, Fernández Fernández et al. [89] found that research and development spending is negatively associated with CO2 emissions in the European Union, the United States and China between 1990 and 2013, suggesting that R&D spending leads to CO2 emissions. Using firm-level data, Lee and Min [90] demonstrated a negative link between green R&D investment and carbon emissions.

Furthermore, a country's development level could have played an essential role in allocating resources for innovation and green innovation. For instance, the Environmental Kuznets Curve (EKC) hypothesis [91–93] argues that countries would experience improvement in their environmental outcomes after countries surpass a certain development level as they tend to adopt cleaner technologies and countries with higher income would have a higher preference environmental quality (see also Bashir et al. [94], Sarkodie and Strezov [95] and Shahbaz and Sinha [96] for a detailed survey on the EKC hypothesis). Using household data, Schleich [97] showed that the households that fall into the highest income quartile have higher adoption of energy-efficient technologies than those of the lowest income quartile households. In other words, countries with higher development levels may have adopted cleaner technologies (i.e., higher green patents) and are more likely to belong to a more innovative club.

Institutional quality and protection of property rights are also important determinants of innovation (see e.g., Ref. [98–100]), and the number of patent applications is positively associated with institutional quality. Furthermore, institutional quality is a critical determinant of renewable energy consumption. Chen et al. [101] demonstrated that institutions are vital in channeling economic resources to renewable energy technology and promoting a higher proportion of renewable energy consumption. Uzar [102] found that institutional quality is positively associated with renewable energy consumption in 38 countries between 1990 and 2015. Islam et al. [103] demonstrated that institutional quality promoted renewable energy in Bangladesh between 1990 and 2019 using a dynamic ARDL approach.

It has been found that environmental regulations are a viable tool to reduce greenhouse gas emissions (see e.g., Ref. [104–109]), ecological footprint (see e.g. Ref. [110]) and improve energy efficiency (see e.g., Ref. [111,112]). Most existing studies argue that environmental taxes reduce carbon emissions and increase energy efficiency because increased environmental taxes lead to the use of green technologies and innovation. Bashir et al. [111] used panel data covering the 1994–2018 period for 29 OECD countries and demonstrated that the environmental tax increases energy efficiency by promoting green innovation. Neves et al. [106] found that the environmental regulations and policies supporting renewable energy consumption help reduce CO2 emissions. Using panel data for 29 OECD countries between 1994 and 2016, Rafique et al. [110] demonstrated that environmental taxes reduced the ecological footprint by using efficient technologies. Using panel data from 14 OECD countries over the period 1990–2011, Martínez-Zarzoso et al. [113] showed that stringent environmental regulations promote a higher number of patent applications in OECD countries. Similarly, using panel data from high and middle-income 42 countries covering the period between 1995 and 2018, Karmaker et al. [114] showed that environmental taxes increased environment-related technological innovation in these countries. Furthermore, the existing literature also used energy efficiency and renewable energy regulation indicators are used to assess their role in energy efficiency and CO2 emission reductions (see e.g., Gunnarsdottir et al. [115] and Neofytou et al. [116] for review of regulation indicators).

Human capital is also an important ingredient for innovation (e.g., Ref. [117–123]). Diebolt and Hippe [119] showed that human capital played a significant role in explaining the current differences in innovation and economic development in the European Union. Using historical data, Cinnirella and Streb [118] demonstrated that human capital accumulation played a significant role in patent applications in Prussia. McGuirk et al. [121] and Protogerou et al. [122] showed that firms employing managers with innovative human capital are more likely to innovate using European firm-level data. Consoli et al. [124] found that human capital is used more intensively in greener jobs than in non-green jobs. Scarpellini et al. [125] also showed that human capital plays a significant role in adaptation eco-innovation.

Finally, CO2 emissions, energy intensity, and renewable energy may have played an essential role in promoting environmentally friendly technologies. Countries with relatively higher CO2 emissions and energy intensity may invest more in green technologies to improve their energy efficiency and decrease CO2 emissions. On the other hand, countries with higher levels of renewable energy consumption may have a good level of renewable energy deployment to promote green innovation as

[2] The methodological details of the Probit/Logit models are not provided due to space limitations; however, one could refer to the listed set of academic references that used these models for further details.

there is a greater demand for these technologies.

We obtained the explanatory variables from different sources. We obtained GDP per capita (measured in constant US dollars, 2015), CO2 emissions (measured in metric tons per capita), renewable energy consumption (measured as the percentage of total final energy consumption), the energy intensity level of primary energy (MJ/$2017 PPP GDP), R&D investment expenditure (measured as the percentage of the GDP), and human capital (measured as the percentage of population ages 25 and over that attained or completed upper secondary education) from World Development Indicators of the World Bank [126]. On the other hand, we use the rule of law component from the World Governance Indicators of the World Bank [127] as a proxy for institutional quality. Finally, we use the average of the renewable energy and energy efficiency regulation indices from the Regulatory Indicator for Sustainable Energy (RISE) of the World Bank [128] as an environmental regulation proxy (see Neofytou et al. [116] for the use of the regulation indicators). These indices assess a country's policies and regulations to promote renewable energies and energy efficiency and range from 0 to 100, 100 being very conductive policies and regulations (see Ref. [129] for the details of the indicators).

Since the Probit/Logit regression analysis requires cross-sectional data, explanatory variables are averaged using the data between 1993 and 2018 rather than selecting a particular year for analysis.[3]

## 4. Results

### 4.1. Convergence clubs and the determinants of final convergence clubs

Table 3 shows the club convergence results. Firstly, since the t-statistic (i.e., −8.629) is lower than the critical t-value (i.e., −1.65), the null hypothesis of convergence is rejected at the 5 % level. Hence, we carry out the second to fourth stages of the algorithm to identify convergence clubs. Furthermore, as recommended by Phillips and Sul [20] and Schnurbus et al. [76], and as part of the fifth stage of the algorithm, the club merging procedure is carried out to examine whether two subsequent initial clubs may be merged. The merging club statistics are reported in Table 3. The t statistic was obtained by performing the joint log t regression test on the initial Clubs 1 and 2, which is −8.629. As the t-statistics is lower than the critical t-value of −1.65, convergence clubs 1 and 2 cannot be merged. Therefore, final convergence clubs are identified and reported in Table 3. The first and second club consists of 33 and 57 countries, respectively.

When we examine the average GREI between 1993 and 2018 in each final convergence club, we observe that the first final convergence club had relatively higher GREI, and the second final convergence club had low GREI levels. For instance, on average, a country that belongs to final convergence club 1 had 180 green and renewable energy technology patents per year. On the other hand, a country that belongs to final convergence club 2 had 0.7 green and renewable energy patents per year. Therefore, there is a clear distinction between the two convergence clubs.

Next, we will examine the factors that explain the probability/likelihood of belonging to a particular final convergence club by using the Probit/Logit models. However, before using the Probit/Logit models, we first check the correlation among explanatory variables. Multicollinearity is an important problem for the Probit/Logit [130] or linear estimation methods [131] as it could increase the standard errors of the regression coefficient estimates and regression coefficients become sensitive to the model specifications. Therefore, similar to the previous literature (see e.g., Ref. [63,68,78]), before carrying out Probit/Logit

**Table 3**
Convergence in REI.

| Initial classification | | Club merger tests | | Final classification |
|---|---|---|---|---|
| Full sample [90] | | | | |
| Coefficient | t-stat | | | |
| −0.457 | −8.629 | | | Club 1: Australia, Austria, Belgium, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, India, Ireland, Israel, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Poland, Russia, Saudi Arabia, Singapore, Slovak Republic, Spain, Sweden, Switzerland, Taiwan, Thailand, Türkiye, United Kingdom, United States |
| Club 1 [33] | | Club 1 + 2 [90] | | |
| Coefficient | t-stat | Coefficient | t-stat | |
| −0.019 | −0.206 | −0.457 | −8.629 | |
| Club 2 [57] | | | | Club 2: Algeria, Argentina, Armenia, Belarus, Bosnia Herzegovina, Bulgaria, Colombia, Costa Rica, Croatia, Cuba, Cyprus, Czech Republic, Ecuador, Egypt, El Salvador, Estonia, Georgia, Greece, Guatemala, Hong Kong, Hungary, Iceland, Indonesia, Iran, Jamaica, Jordan, Kazakhstan, Kenya, Kuwait, Latvia, Lebanon, Lithuania, Luxembourg, Malaysia, Malta, Mexico, Moldova, Mongolia, Morocco, Nigeria, North Macedonia, Pakistan, Panama, Peru, Philippines, Portugal, Romania, Slovenia, South Africa, Sri Lanka, Trinidad and Tobago, Tunisia, Ukraine, United Arab Emirates, Uruguay, Uzbekistan, and Zimbabwe |
| Coefficient | t-stat | | | |
| −0.119 | −0.871 | | | |

regression analyses, we provide the correlation matrix for the explanatory variables in Table 4 to identify highly correlated explanatory variables. Overall, we find that some of the explanatory variables are highly and significantly correlated, and one should consider this while carrying out the Probit/Logit regression analyses to overcome multicollinearity problems. Finally, it should be noted that we use the natural logarithm of the GDP per capita, CO2 emissions per capita, renewable energy consumption, energy intensity, environmental regulation and education. These variables are skewed, and we transform them with the natural logarithm to reduce variance-covariance matrix variation and heteroscedasticity and transform the skewed data into normal distribution (see e.g., Ref. [132,133]).

Tables 5 and 6 provide the estimation results obtained with the Probit and Logit models, respectively. In these analyses, the dependent variable equals 1 if the country belongs to a more innovative club (club 1) and zero if the country belongs to a less innovative club (club 2). In other words, the reference class is the final club 2. Columns (1) of Tables 5 and 6 offer the results when all the regressors are included in the analysis. When we include all the explanatory variables in the estimation, the explanatory power of the model is high (i.e., pseudo R-squares are 0.56 and 0.55 with the Probit and Logit models, respectively), but only the coefficient of the R&D expenditure is significant at the 5 % level, which is considered as one of the consequences of the multicollinearity problem [131]. Therefore, to overcome the multicollinearity problem, we used a different set of explanatory variables in the analyses by excluding some highly correlated variables. The findings in columns (2)–(5) of Tables 5 and 6 suggest that GDP per capita, CO2 emissions, R&D expenditure, rule of law and environmental regulation significantly increase the probability of being in the innovative club as opposed to the less innovative club. Columns (6)–(10) of Tables 5 and 6

[3] The data on institutional quality and environmental regulation proxies are available from 1996 to 2010. Therefore, we obtain the averages of institutional quality (environmental regulation) variables between 1996 (1990) and 2018, respectively.

**Table 4**
Correlation matrix.

| | GDP | CO2 | REC | R&D | RL | REG | EI | HC |
|---|---|---|---|---|---|---|---|---|
| GDP | 1 | | | | | | | |
| CO2 | 0.663*** | 1 | | | | | | |
| REC | −0.152 | −0.479*** | 1 | | | | | |
| R&D | 0.689*** | 0.414*** | −0.113 | 1 | | | | |
| RL | 0.819*** | 0.517*** | −0.183* | 0.734*** | 1 | | | |
| TAX | 0.512*** | 0.343*** | −0.247** | 0.593*** | 0.667*** | 1 | | |
| EI | −0.176* | 0.168 | −0.012 | −0.078 | −0.287*** | −0.187 | 1 | |
| HC | 0.367*** | 0.376*** | −0.336*** | 0.447*** | 0.426*** | 0.308*** | 0.129 | 1 |

GDP: GDP per capita; CO2: CO2 emissions per capita; REC: Renewable energy consumption; R&D: R&D expenditure; RL: Rule of law; REG: Environmental regulation; EI: Energy intensity; HC: Human capital.

**Table 5**
Probit regression results.

| | Coefficients | | | | | Marginal effects | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 |
| GDP | −0.017 | 0.763*** | | | | −0.006 | 0.280*** | | | |
| | (0.619) | (0.182) | | | | (0.241) | (0.066) | | | |
| CO2 | 0.007 | | 0.720*** | | | 0.003 | | 0.268*** | | |
| | (0.714) | | (0.275) | | | (0.278) | | (0.098) | | |
| REC | −0.016 | 0.120 | | −0.083 | 0.004 | −0.006 | 0.044 | | −0.032 | 0.001 |
| | (0.208) | (0.0932) | | (0.098) | (0.089) | (0.081) | (0.034) | | (0.038) | (0.032) |
| R&D | 1.948** | | | 1.583*** | | 0.759** | | | 0.611*** | |
| | (0.850) | | | (0.332) | | (0.295) | | | (0.136) | |
| RL | 0.676 | | | | 0.977*** | 0.263 | | | | 0.356*** |
| | (0.494) | | | | (0.217) | (0.193) | | | | (0.078) |
| REG | −0.221 | | 1.199*** | | | −0.086 | | 0.447*** | | |
| | (0.626) | | (0.442) | | | (0.241) | | (0.159) | | |
| EI | 0.411 | 0.267 | −0.679 | −0.301 | 0.341 | 0.160 | 0.098 | −0.253 | −0.116 | 0.124 |
| | (1.048) | (0.361) | (0.473) | (0.410) | (0.375) | (0.409) | (0.132) | (0.176) | (0.159) | (0.136) |
| HC | −0.642 | −0.035 | 0.152 | −0.476 | −0.168 | −0.250 | −0.013 | 0.057 | −0.184 | −0.061 |
| | (0.643) | (0.416) | (0.487) | (0.472) | (0.429) | (0.253) | (0.153) | (0.182) | (0.182) | (0.156) |
| Log likelihood | −21.905 | −42.615 | −33.876 | −32.423 | −40.821 | | | | | |
| LR test statistic | 55.11 | 27.36 | 33.48 | 45.83 | 30.95 | | | | | |
| LR test (probability) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | | | | | |
| Pseudo R2 | 0.5571 | 0.2430 | 0.3307 | 0.4141 | 0.2749 | | | | | |
| Observations | 72 | 85 | 74 | 83 | 85 | | | | | |

Notes: Standard errors are reported in parentheses. Constant is included but not reported. ***, **, * represent significance at the 1 %, 5 % and 10 % level, respectively. GDP: GDP per capita; CO2: CO2 emissions per capita; REC: Renewable energy consumption; R&D: R&D expenditure; RL: Rule of law; REG: Environmental regulation; EI: Energy consumption; HC: Human capital.

offer the marginal effects. The findings suggest that the countries with higher GDP per capita, CO2 emissions, R&D expenditure, and stricter environmental regulation and better institutional quality have a higher probability/likelihood of being in a more innovative club (i.e., final club 1) as opposed to a less innovative club (i.e., final club 2).

The findings presented in Tables 5 and 6 align with the existing empirical findings. Our findings highlight that richer countries allocate more resources to innovative activities and innovate more. The findings align with the EKC hypothesis as countries that surpass a certain development level innovate and adapt cleaner technologies [94–96, 134]. Furthermore, it has been found that countries with better institutional quality have a higher probability/likelihood of belonging to more innovative club. This finding also aligns with the existing literature. It has been found that the countries with better institutional quality innovate more [98–100] and have higher shares of renewable energy consumption (Chen et al., 2021b; Uzar, 2020; Islam et al., 2022). On the other hand, our findings suggest that the countries with better environmental regulation have a higher probability/likelihood of belonging to a more innovative club, which aligns with the literature because environmental regulation promotes green and renewable energy innovation (see e.g., Ref. [111,113]). Countries with higher CO2 emissions per capita have a higher probability/likelihood to be in more innovative clubs. This could be because countries with high emissions are pressured to innovate and use renewable energy technologies to reduce their emissions. Finally, countries with higher R&D investment have a higher probability of belonging to an innovative club because R&D investment promotes innovation [16,88].

### *4.2. Robustness analysis*

Our findings reported in Tables 5 and 6 identified that the countries with higher income per capita have a higher probability/likelihood of belonging to a club with higher REI. This is in line with the idea that the technological progress and adaptation of clean technologies are expected to be higher in high-income countries based on the environmental Kuznets curve hypothesis (see e.g. Ref. [94,96], for a detailed review of environmental Kuznets curve). Therefore, we also examine convergence in REI for countries belonging to different income groups based on the World Bank income classification. The results of the convergence in REI for the low-middle, upper-middle and high-income groups are presented in Tables 7–9, respectively.

Low-middle, upper-middle and high-income groups consisted of 18, 25 and 47 countries, and the results suggest that there is no absolute convergence in REI for low-middle, upper-middle and high-income countries as full sample test statistics (i.e., −4.453, −9.036 and −5.511 for respective income groups) were lower than the critical t-value of −1.65. The results indicate two final convergence clubs for the low-middle-income countries (Table 4). India and the Philippines belong to the first final convergence club, and the rest of the low-middle-income countries are listed in the second one. We also found two final

**Table 6**
Logistic regression results.

| | Coefficients | | | | | Marginal effects | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 |
| GDP | −0.0708 | 1.348*** | | | | −0.017 | 0.298*** | | | |
| | (1.062) | (0.353) | | | | (0.254) | (0.077) | | | |
| CO2 | 0.0269 | | 1.188** | | | 0.006 | | 0.270** | | |
| | (1.249) | | (0.504) | | | (0.299) | | (0.110) | | |
| REC | −0.0246 | 0.210 | | −0.131 | 0.0202 | −0.006 | 0.046 | | −0.031 | 0.004 |
| | (0.372) | (0.171) | | (0.175) | (0.158) | (0.089) | (0.038) | | (0.042) | (0.035) |
| R&D | 3.351** | | | 2.732*** | | 0.801** | | | 0.655*** | |
| | (1.495) | | | (0.634) | | (0.299) | | | (0.164) | |
| RL | 1.128 | | | | 1.667*** | 0.270 | | | | 0.366*** |
| | (0.873) | | | | (0.413) | (0.210) | | | | (0.088) |
| REG | −0.387 | | 2.001** | | | −0.093 | | 0.454** | | |
| | (1.111) | | (0.835) | | | (0.261) | | (0.182) | | |
| EI | 0.636 | 0.496 | −1.177 | −0.418 | 0.605 | 0.152 | 0.110 | −0.267 | −0.100 | 0.133 |
| | (1.835) | (0.663) | (0.804) | (0.734) | (0.694) | (0.440) | (0.147) | (0.182) | (0.176) | (0.153) |
| HC | −1.085 | −0.0244 | 0.292 | −0.891 | −0.347 | −0.259 | −0.005 | 0.066 | −0.214 | −0.076 |
| | (1.201) | (0.743) | (0.850) | (0.843) | (0.789) | (0.292) | (0.164) | (0.194) | (0.202) | (0.173) |
| Log likelihood | −22.348 | −42.250 | −34.036 | −32.599 | −40.854 | | | | | |
| LR test statistic | 54.23 | 28.09 | 33.16 | 45.48 | 30.88 | | | | | |
| LR test (probability) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | | | | | |
| Pseudo R2 | 0.5482 | 0.2495 | 0.3275 | 0.4109 | 0.2743 | | | | | |
| Observations | 72 | 85 | 74 | 83 | 85 | | | | | |

Notes: Standard errors are reported in parentheses. Constant is included but not reported. ***, **, * represent significance at the 1 %, 5 % and 10 % level, respectively. GDP: GDP per capita; CO2: CO2 emissions per capita; REC: Renewable energy consumption; R&D: R&D expenditure; RL: Rule of law; REG: Environmental regulation; EI: Energy consumption; HC: Human capital.

**Table 7**
Convergence in REI for low middle income group countries and final convergence clubs.

| Initial classification | | Club merger tests | | Final classification |
|---|---|---|---|---|
| Full sample [18] | | | | |
| Coefficient | t-stat | | | |
| −0.865 | −4.453 | | | Club 1: India and the Philippines |
| Club 1 [2] | | Club 1 + 2 [18] | | |
| Coefficient | t-stat | Coefficient | t-stat | |
| −0.464 | −1.616 | −0.865 | −4.453 | |
| Club 2 [16] | | | | Club 2: Algeria, Egypt, El Salvador, Indonesia, Iran, Kenya, Lebanon, Mongolia, Morocco, Nigeria, Pakistan, Sri Lanka, Tunisia, Ukraine, Uzbekistan, and Zimbabwe |
| Coefficient | t-stat | | | |
| n/a | n/a | | | |

n/a represents not applicable.

**Table 8**
Convergence in REI for high middle income group countries and final convergence clubs.

| Initial classification | | Club merger tests | | Final classification |
|---|---|---|---|---|
| Full sample [25] | | | | |
| Coefficient | t-stat | | | |
| −0.810 | −9.036 | | | Club 1: Argentina, Armenia, Brazil, Bulgaria, Jordan, Kazakhstan, Malaysia, Mexico, Peru, Russia, South Africa, Thailand and Türkiye |
| Club 1 [13] | | Club 1 + 2 [24] | | |
| Coefficient | t-stat | Coefficient | t-stat | |
| −0.093 | −0.735 | −0.418 | −4.403 | |
| Club 2 [11] | | Club 2 + 3 [12] | | Club 2: Belarus, Bosnia Herzegovina, Colombia, Costa Rica, Cuba, Ecuador, Georgia, Guatemala, Jamaica, Moldova and North Macedonia |
| Coefficient | t-stat | Coefficient | t-stat | |
| n/a | n/a | −1.245 | −14.325 | |
| Club 3 [1][a] | | | | Club 3: China |

[a] Represents non-convergent club; n/a represents not applicable.

**Table 9**
Convergence in REI for high income group countries and final convergence clubs.

| Initial classification | | Club merger tests | | Final classification |
|---|---|---|---|---|
| Full sample [47] | | | | |
| Coefficient | t-stat | | | |
| −0.370 | −5.511 | | | Club 1 [27]: Australia, Austria, Belgium, Canada, Chile, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Poland, Saudi Arabia, Singapore, Slovak Republic, Spain, Sweden, Switzerland, Taiwan, United Kingdom and United States |
| Club 1 [9] | | Club 1 + 2 [20] | | |
| Coefficient | t-stat | Coefficient | t-stat | |
| 0.413 | 2.887 | 0.034 | 0.339 | |
| Club 2 [11] | | Club 2 + 3 [18] | | Club 2 [20]: Croatia, Cyprus, Czech Republic, Estonia, Greece, Hong Kong, Hungary, Iceland, Kuwait, Latvia, Lithuania, Luxembourg, Malta, Panama, Portugal, Romania, Slovenia, Trinidad and Tobago, United Arab Emirates and Uruguay |
| Coefficient | t-stat | Coefficient | t-stat | |
| 0.028 | 0.198 | −0.035 | −0.281 | |
| Club 3 [7] | | Club 3 + 4 [27] | | |
| Coefficient | t-stat | Coefficient | t-stat | |
| 0.192 | 0.338 | −0.327 | −3.464 | |
| Club 4 [20] | | | | |
| Coefficient | t-stat | | | |
| −0.129 | −0.847 | | | |

convergence clubs for the upper-middle income countries and a divergent club (i.e., China), and clubs 1 and 2, and clubs 2 and 3 cannot be merged as the t-statistics are lower than the critical value. Finally, for the high-income countries, initial convergence analysis identified four convergence clubs. However, when we carried out tests to examine whether we could merge the consecutive clubs (i.e., clubs 1 and 2, clubs 2 and 3, and clubs 3 and 4), our findings highlight that clubs 1 and 2, and clubs 2 and 3 could be merged as the respective t-statistics (i.e., 0.339 and −0.281) are higher than critical t-value. On the other hand, the t-statistic of the merger tests of convergence of clubs 3 and 4 is −3.464, which is less than −1.65, suggesting that these two clubs cannot be merged. In other words, the initial first three clubs are combined into a single club, which is presented as final convergence club 1 in Table 9. Countries that belong to final convergence clubs 1 in different income categories have higher REI than final convergence clubs 2. On the other hand, a non-divergent club in the high middle-income category (i.e., China) has significantly higher REI than the rest of the countries in this category.

Overall, final convergence clubs for different income groups mostly align with those obtained for the whole sample. For instance, all countries listed in final convergence clubs 1 and 2 for high-income countries are also listed in final convergence clubs 1 and 2 for the whole sample. Similarly, all the countries listed in final convergence club 1 with the entire sample analysis but not part of the high-income countries (i.e., Brazil, India, Russia, Thailand, and Turkey) are also listed as part of the final convergence club 1 for low and high-middle-income countries. However, some countries are listed in different final convergence clubs when the analysis is carried out for different income categories compared to the whole sample. Argentina, Armenia, Bulgaria, Jordan, Kazakhstan, Malaysia, Mexico, Peru, Philippines and South Africa are listed in final convergence clubs 1 for the low and high-middle-income countries. However, these countries were listed in final convergence club 2 in the whole sample analysis.

Most of the final convergence clubs obtained for different income categories align with the ones obtained for the whole sample scenario. However, we also find that the analysis based on different sets of countries may result in distinctive final convergence clubs. Since the convergence algorithm of Phillips and Sul [19,20] relies on relative convergence, this finding is not surprising. However, the findings highlight that future studies employing this methodology should also provide robustness analysis based on different country samples.

## 5. Conclusions and policy implications

Countries aim to reduce their CO2 emissions and improve their energy efficiency to mitigate the negative implications of climate change. One way of achieving these goals is to innovate green and renewable energy technologies as these technologies have been found to be an effective way of reducing CO2 emissions (see e.g., Ref. [7,28]) and energy intensity (see e.g., Ref. [4,34]). Therefore, designing innovation policy requires convergence analysis in REI. Therefore, this paper examined the convergence in REI for 90 countries for the 1993–2018 period by employing the convergence algorithm proposed by Philips and Sul [19,20]. This paper also used Logit/Probit models to examine factors contributing to the likelihood/probability of belonging to a particular final convergence club.

The paper's findings highlight that there is no absolute convergence in REI for 90 countries. The convergence algorithm reveals that there are two final convergence clubs for REI: i) final convergence club 1 (i.e., a club that consists of countries with high REI) and ii) final convergence club 2 (i.e., a club with countries that have low REI). The findings highlight that even though REI across 90 countries does not converge, REI in two final clubs converges. The robustness analysis for countries in different income categories also reveals two distinctive final convergence clubs in each income category, highlighting the fact that convergence clubs could vary based on the country sample (see e.g. Ref. [12], for convergence in renewable energy consumption for different country groups). Finally, the results from the Probit/Logit models suggest that countries with higher GDP per capita, CO2 emissions, R&D spending, and better environmental regulations and institutional quality have a higher probability/likelihood of belonging to the final convergence club with higher REI.

The findings of this paper have various policy implications. Firstly, countries have different convergence paths in REI, suggesting that some countries tend to innovate more of green technologies (final convergence club 1) and other countries tend to innovate less (final convergence club 2) and green technology innovations between these two clubs do not converge. Therefore, there should be worldwide policy coordination to ensure the diffusion of renewable energy technologies across countries to use more renewable energy. Secondly, governments of countries that belong to the less innovative clubs (final convergence club 2) could promote policies that would increase firm-level technology absorption and diffusion of green and renewable energy technologies through foreign direct investment (see e.g. Ref. [38]). In other words, given the lack of REI by some countries, these countries should take policy actions to increase the exchange and incorporation of green and renewable energy technologies.

The findings also suggest that the countries with higher GDP per capita, CO2 emissions, R&D spending, and better environmental regulations and institutional quality have a higher probability/likelihood of belonging to the final convergence club with higher REI. Therefore, countries should aim to increase their R&D spending and improve their environmental regulations and institutional quality to increase their likelihood of belonging to more innovative club. Firstly, governments should impose strict environmental regulations to increase the use of green technologies and green innovation. Governments could increase environmental taxes to increase energy efficiency and renewable energy deployments [111]. The governments could also prioritize environmental regulations and policies [106]. For instance, governments should promote a legal framework for increasing renewable energy consumption, implement carbon pricing, and subsidize renewable energy technologies. Secondly, countries should improve their institutional quality capacity and the protection of property rights through their legal framework. Countries with stronger institutional quality promote higher renewable energy consumption [102,103,135] by channeling more economic resources to renewable energy consumption [101]. Thirdly, the governments should increase R&D investment in renewable energy technologies (Bai et al., 2022) and offer financial incentives for firms to increase green R&D investments by firms [90].

There are various extensions to this study. Firstly, a similar methodology could be used to examine the convergence in REI for different country samples (e.g., the European Union) to provide specific policy recommendations for a set of countries. Secondly, an additional set of explanatory variables could be used to examine the factors that explain the probability/likelihood of belonging to a specific final convergence club. Finally, a future study could also examine the convergence in REI at the firm level to examine the potential diffusion of green technologies within and across countries.

## Data availability

The data in this article can be obtained through publicly available resources or communication with the corresponding author.

## CRediT authorship contribution statement

**Mehmet Pinar:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, preparation, Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix

**Table A1**
List of countries

| | | | | | |
|---|---|---|---|---|---|
| Algeria | Croatia | Hong Kong | Kuwait | Norway | Sri Lanka |
| Argentina | Cuba | Hungary | Latvia | Pakistan | Sweden |
| Armenia | Cyprus | Iceland | Lebanon | Panama | Switzerland |
| Australia | Czech Republic | India | Lithuania | Peru | Taiwan |
| Austria | Denmark | Indonesia | Luxembourg | Philippines | Thailand |
| Belarus | Ecuador | Iran | Malaysia | Poland | Trinidad Tobago |
| Belgium | Egypt | Ireland | Malta | Portugal | Tunisia |
| Bosnia Herzegovina | El Salvador | Israel | Mexico | Romania | Türkiye |
| Brazil | Estonia | Italy | Moldova | Russia | Ukraine |
| Bulgaria | Finland | Jamaica | Mongolia | Saudi Arabia | UAE |
| Canada | France | Japan | Morocco | Singapore | United Kingdom |
| Chile | Georgia | Jordan | Netherlands | Slovak Republic | United States |
| China | Germany | Kazakhstan | New Zealand | Slovenia | Uruguay |
| Colombia | Greece | Kenya | Nigeria | South Africa | Uzbekistan |
| Costa Rica | Guatemala | Korea | N. Macedonia | Spain | Zimbabwe |

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