Science of the Total Environment 785 (2021) 147257

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Escalation effect of fossil-based CO_2 emissions improves green energy innovation

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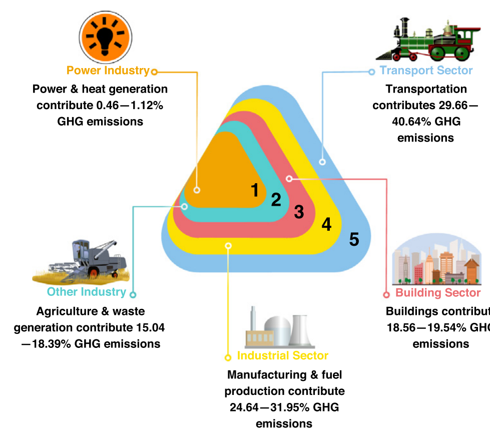
HIGHLIGHTS

- We explore the effect of fossil-based CO_2 emissions in improving green energy innovation.
- We apply econometric and machine learning techniques to assess complexities in emissions.
- We identify winners and losers of environmental sustainability through hotspot ranking.
- We develop both aggregate emissions and economic sectoral fossil-based models.
- Countries with historical green energy orientation invest over 58% more in achieving green growth.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 18 March 2021
Received in revised form 11 April 2021
Accepted 16 April 2021
Available online 22 April 2021

Editor: Pavlos Kassomenos

Keywords:
Green energy innovation
Climate change mitigation
Energy research and development
GHG emissions

ABSTRACT

The 21st-century development pathway is facing a challenge between climate change mitigation, sustained economic prosperity, and energy security. While extant literature focuses on drivers of anthropogenic emissions, the role of policy measures including green energy innovation, and energy research and development are limited in scope. Here we develop conceptual tools across IEA member countries with four decades of data that demonstrate the role of green energy innovation, and research and development in reducing emissions. Our assessment reveals that sectoral fossil-based CO_2 contributes directly to GHG emissions by 29.7–40.6% from transport, 24.6–32% from industry, 18.6–19.5% from buildings, 15–18.4% from other sectors, and 0.5–1.1% from power. We highlight that industrialized high-income countries converge on green energy innovation but diverge on emissions. The empirical evidence shows that achieving green growth is possible through green energy innovation amidst climate change and its impact.

1. Introduction

Climate change has become a global concern due to its longstanding impact on the biosphere. Adverse effects of climate change include variability in weather patterns leading to extreme conditions and events such as flooding, hunger, earthquake, tsunamis, wildfires, drought, and sea-level rise (Bowman et al., 2020; Bronselaer and Zanna, 2020; Fujimori et al., 2019; Trnka et al., 2014). However, climate change is inevitable owing to natural occurrences, increasing population, urban sprawl, growing energy, food, and water demands (Meehl et al., 2007). Nevertheless, the rate of biospheric deterioration driven by human activities can be curtailed through emission-reduction strategies (Meckling and Allan, 2020; Meckling et al., 2017).

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https://doi.org/10.1016/j.scitotenv.2021.147257

Energy intensity and fossil fuels are fundamental drivers of anthropogenic emissions, hence, mitigating climate change entails structural adjustment in energy systems––where renewables and new technologies can improve energy efficiency (IEA, 2020). Majority of emissions come from sectors including buildings, industry, other sectors, power industry, and transport––with limited technological advancement. Decarbonization of these sectors requires technological advancement and innovation that improve sectoral efficiency while reducing energy intensity and emissions (Rockström et al., 2017). Efficient end-use technologies––where energy conversion drives economic development––are reported to contribute largely to emission reduction compared to energy-supply technologies. Similarly, end-use technologies provide relatively high social benefits, viz. environmental, economic, and energy security returns on technological investment compared to energy-supply technologies (Wilson et al., 2012).

While there is no single pathway towards achieving net-zero emissions, adoption of green energy innovation can accelerate the agenda towards environmental sustainability (IEA, 2020). Global energy research and development spending increased by 3% (i.e., US$ 30 billion) in 2019 with 80% of the budget allocated to low-carbon and clean energy technologies (IEA, 2020). While several countries allocate high budgets for research and development, very little is known about the effect of research and development on green energy innovation, and sectoral-fossil-based GHG emissions. The existing studies have explored the immediate driving forces of anthropogenic emissions (Le Quéré et al., 2019; Rosa and Dietz, 2012; Schmidt and Sewerin, 2017), however, very few studies have assessed underlying drivers of emissions––whereas studies on policy-drivers of GHG emissions are limited. Policy drivers including green energy innovation and energy research and development act as abatement strategies of global emissions (Meng et al., 2020; Sarkodie et al., 2021). In a century of carbon and energy-intensive economic growth trajectory, studies on green energy innovation are useful in achieving decarbonized and energy-efficient growth while mitigating GHG emissions and its impacts (D'Alessandro et al., 2020; Wilson et al., 2012).

Owing to limitations and sporadicity of existing literature on green energy, this study contributes to the global debate by exploring the effect of fossil-based CO_2 emissions in improving green energy innovation in 21 industrialized high-income countries using annual occurrence data from 1975 to 2014. We use a novel convergence estimation method to classify industrialized high-income IEA member countries into similar emission, and energy transition pathways. We apply both econometric and machine learning techniques to investigate the complexities of anthropogenic emissions and develop conceptual tools valuable for policy design. The novel techniques include panel-bootstrap bias-corrected fixed-effects, panel-kernel regularized least-squares, panel log-t regression-based convergence, panel threshold fixed-effects, and dynamic ARDL stochastic simulations. The selection of the estimation tools is useful in controlling for historical and inertial effects, transboundary correlation, heterogeneity, fixed-effects, omitted-variable bias, and misspecification bias. We examine the heterogeneous effects of anthropogenic emissions, green energy innovation, energy intensity, energy research and development, and service-based industrial structure. We estimate the forty-year trend of emissions and policy measures across countries and identify winners and losers of environmental sustainability through hotspot identification and ranking. We develop both aggregate emissions and economic sectoral fossil-based (buildings, power, industry, transport, and other sectors) models to explore the effects of immediate, underlying drivers, and policy measures. We predict the counterfactual change in GHG emissions from 2014 to 2064 using the business-as-usual scenario of 1% growth in energy intensity across IEA member countries. Our study demonstrates that investment and integration of green energy innovation, energy research and development, and expansion of service-based industrial structure have mitigating effects on GHG emissions. Our prediction model reveals that 1% shock in energy intensity will increase GHG emissions by over 5.56% in 2064. Further evidence shows fossil CO_2 emissions from IEA member countries with high GHG emission levels have a positive relationship with green energy innovation. The empirical analysis suggests countries with historical green energy orientation may invest over 58% more in achieving green growth through green innovation. Thus, countries with higher GHG emissions like the US may perhaps improve green energy innovation in efforts towards achieving environmental sustainability while sustaining economic prosperity.

2. Methods

Our cross-country time series estimation modeling is based on data spanning 1975–2014—retrieved from IEA, OECD, World Bank, and EDGAR databases. Due to periodic data limitations and completeness, our data comprise 21 industrialized high-income countries from 30 IEA member blocs. The selected countries in ISO 31661—alpha-3 code include AUS, AUT, BEL, CAN, CHE, DEU, DNK, ESP, FIN, FRA, GBR, GRC, IRL, ITA, JPN, NLD, NOR, NZL, PRT, SWE, and USA. The sustainable development agenda underpins the numerous indicators selected for this study. From energy and environmental policy perspective, the utilization of aggregated fossil fuel-based CO_2 limits the specificity of sectoral contributions towards anthropogenic emissions, hence, hamper climate control frameworks. We adopt disaggregate fossil-based CO_2 namely industry, power, buildings, transport, and other sectors (agriculture and waste) (Crippa et al., 2019). Data on energy research and development are adopted via a perpetual system of stock inventory (Chakraborty and Mazzanti, 2020). Total patent counts from OECD-categorized GHG abatement technologies (carbon capture, storage, and sequestration) and service-based gross domestic product are used as surrogates for assessing green energy innovation and industrial structure following the extant literature (Popp et al., 2011). Green energy innovation is defined herein as energy-based innovations, technologies, and practices with emission reduction effect. The selection of service-based GDP as indicator for industrial structure stems from the popular environmental Kuznets curve hypothesis. It is assumed that the economic structure of sampled countries shifts towards energy efficiency and environmental sustainability (Sarkodie and Strezov, 2019). In this regard, our a priori expects a negative parameter as a sign towards emission reduction. Second, the inclusion of services is essential to curtail omitted-variable bias—as other economic sectoral indices namely agriculture and industry are accounted for. Our empirical assessment includes several empirics, metrics, and structural adjustments including averages, minimum, maximum, aggregate, disaggregate, ranking, weighting, accounting, machine learning algorithm, and econometric modeling techniques. To achieve a constant variance of sampled variables across countries regardless of population and economic structure, we applied log transformation.

To estimate the compound annual growth rate of sectoral-based fossil CO_2 emissions, we use the mathematical expression:

$$FCO_{2,i}(t_0, t_T) = \left(\frac{SFCO_{2,j}(t_T)}{SFCO_{2,j}(t_0)}\right)^{\frac{1}{t_T - t_0}} - 1 \tag{1}$$

where FCO_2 is the compound annual growth rate of fossil-based CO_2 across countries i and sectoral emissions j, t_0 and t_T are the initial and final years of emission trends considered, $SFCO_{2,\,j}(t_T)$ is the final input of sectoral fossil-based CO_2 whereas $SFCO_{2,\,j}(t_0)$ is the initial input of sectoral fossil-based CO_2 emissions. Using the specified mathematical expression allows circumventing periodical volatilities that affect arithmetic comparisons between countries and sectoral emissions using means (Chan, 2009).

Traditional cross-country time series estimation techniques used in empirical assessment fail to account for global common shocks, spillover, and heterogeneous effects across countries. Failure to observe such comprehensive empirical procedure renders statistical inferences spurious. The Covid-19 pandemic accentuates the importance of accounting for global events with long-term transboundary effects (Sarkodie and Owusu, 2021). We implement robust cross-section dependence and homogeneity tests to examine potential transboundary correlation and heterogeneous effects (Ditzen and Bersvendsen, 2020; Pesaran et al., 2008). Several indicators used in empirical assessment often suffer from random-walk properties, hence, exhibit highly persistent characteristics leading to estimation bias. To control this amidst cross-country dependence and heterogeneity, we examine stationarity across sampled indicators using panel-based unit root test from the second generation (Pesaran, 2007). In this regard, data series integrated of order one is first-differenced before model estimation to eliminate potential spurious regression.

2.1. Empirical procedure

We first test convergence using traditional methods to examine the stationarity and cointegration properties of the cross-sectional time series data. However, such estimation procedures are limited in detecting asymptotic long-term relationships (Phillips and Sul, 2007). We initiate the novel estimation approach that examines convergence built on time-varying factors with nonlinear effect. The empirical log-*t* test procedure outweighs conventional techniques by controlling for heterogeneous and evolutional effects without imposing assumptions of stationarity (Phillips and Sul, 2007). The convergence theory posits that all economies of similar industrial and economic structures converge in the long run. The categorization of countries into income groups underpins several emission scenarios, energy, and environmental policies. However, such scenario remains in doubt owing to the heterogeneous distribution and unobserved factors across countries. Thus, rather than using traditional classification of countries to assume potential convergence of industrialized high-income IEA countries, we test for convergence using the empirical procedure expressed as (Du, 2017):

$$TP_{i,t} = \frac{1}{N}\sum_{i=1}^{N}\left(tp_{i,t}-1\right)^2 \to 0 \; if \lim_{t\to\infty}\psi_{i,t} = \psi, for\ i \tag{2}$$

where $TP_{i,\,t}$ is the cross-country variance of the comparative transitional pathway parameter $tp_{i,\,t}$— quantifying the coefficient of the panel means across transitional pathway of countries i at time t. The transitional pathway parameter is estimated by the imposition of restrictions on the time-varying component $\psi_{i,\,t}$ that calculates the distance between the input variable and stochastic term derived from the decomposition of input variable. The null hypothesis of convergence is rejected if the *T*-statistic from the log-*t* test is less than −1.65 after discarding 33.3% of the data fraction before regression (Phillips and Sul, 2007).

Next, we employ panel heterogeneous causality in a bivariate model as a general-to-specific test to examine the predictive power of the sampled series. This procedure is essential to identify the direction of causal influence across divergent countries confirmed from the convergence test (Supplementary Table 1). The novel procedure accounts for both cross-section dependence and heterogeneity, a scenario evident in this study. We apply a panel-based causality estimator using the expression (Dumitrescu and Hurlin, 2012):

$$D_{i,t} = \delta_i + \sum_{k=1}^{K}\lambda_i^{(k)}D_{i,t-k} + \sum_{k=1}^{K}\beta_i^{(k)}I_{i,t-k} + \ \varepsilon_{i,t} \tag{3}$$

where $D_{i,\,t}$ is the target variable, $I_{i,\,t}$ denotes the predictor variable, K is the lag order, δ_i is the country-specific (i) effects fixed over time t, $\lambda_i^{(k)}$ and $\beta_i^{(k)}$signify the autoregressive constraints and slope coefficients of the regression.

Using the predictive components, we assess the determinants of sectoral-based fossil fuel CO_2 expressed as:

$$\begin{aligned}\Delta lnBuildings_{i,t} = {} & \delta_i + \lambda\Delta lnBuildings_{i,t-1} + \gamma_1 Green\ Innovation_{i,t} \\ & + \gamma_2\Delta lnGHG\ Emissions_{i,t} + \gamma_3\Delta Energy\ Intensity_{i,t} \\ & + \gamma_4 lnEnergy\ R\&D_{i,t} + \gamma_5\Delta lnIndustrial\ Structure_{i,t} \\ & + \varepsilon_{i,t}\end{aligned} \tag{4}$$

$$\begin{aligned}\Delta lnIndustry_{i,t} = {} & \delta_i + \lambda\Delta lnIndustry_{i,t-1} + \gamma_1 Green\ Innovation_{i,t} \\ & + \gamma_2\Delta lnGHG\ Emissions_{i,t} + \gamma_3\Delta Energy\ Intensity_{i,t} \\ & + \gamma_4 lnEnergy\ R\&D_{i,t} + \gamma_5\Delta lnIndustrial\ Structure_{i,t} \\ & + \varepsilon_{i,t}\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta lnOther_{i,t} = {} & \delta_i + \lambda\Delta lnOther_{i,t-1} + \gamma_1 Green\ Innovation_{i,t} \\ & + \gamma_2\Delta lnGHG\ Emissions_{i,t} + \gamma_3\Delta Energy\ Intensity_{i,t} \\ & + \gamma_4 lnEnergy\ R\&D_{i,t} + \gamma_5\Delta lnIndustrial\ Structure_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{6}$$

$$\begin{aligned}\Delta lnTransport_{i,t} = {} & \delta_i + \lambda\Delta lnTransport_{i,t-1} + \gamma_1 Green\ Innovation_{i,t} \\ & + \gamma_2\Delta lnGHG\ Emissions_{i,t} + \gamma_3\Delta Energy\ Intensity_{i,t} \\ & + \gamma_4 lnEnergy\ R\&D_{i,t} + \gamma_5\Delta lnIndustrial\ Structure_{i,t} \\ & + \varepsilon_{i,t}\end{aligned} \tag{7}$$

$$\begin{aligned}lnPower_{i,t} = {} & \delta_i + \lambda lnPower_{i,t-1} + \gamma_1 Green\ Innovation_{i,t} \\ & + \gamma_2\Delta lnGHG\ Emissions_{i,t} + \gamma_3\Delta Energy\ Intensity_{i,t} \\ & + \gamma_4 lnEnergy\ R\&D_{i,t} + \gamma_5\Delta lnIndustrial\ Structure_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{8}$$

where Δ and *ln* denote first-difference and logarithmic transformation, δ_i represents heterogeneous effects, that account for unobserved transboundary effects, λ is the estimated parameter of the lagged-dependent variable—which is typically <1—signifying dynamic stability of the relationship. $\gamma_{(..)}$ denotes unknown coefficients of green innovation, GHG emissions, energy intensity, energy R&D, and industrial structure to be estimated. $\varepsilon_{i,\,t}$ is the unobserved error term with *i.i.d.* characteristics, thus, jointly uncorrelated across countries $i = 1, \ldots, 21$ over time $t = 2, \ldots, 40$. While power, green innovation, and energy R&D are level stationary series, buildings, industry, other sectors, transport, GHG emissions, energy intensity, and industrial structure are first-difference stationary series (Table 1). This explains the estimation of Eqs. (4)–(8) with level and first-difference variables. Because emissions have past occurrences that influence current trends, the inclusion of $\Delta lnBuildings_{i,\,t-1}$ in Eq. (4), $\Delta lnIndustry_{i,\,t-1}$ in Eq. (5), $\Delta lnOther_{i,\,t-1}$ in Eq. (6),$\Delta lnTransport_{i,\,t-1}$ in Eq. (7), and $lnPower_{i,\,t-1}$ in Eq. (8) is used as a proxy variable to control for omitted variable bias, and account for unobserved historical factors. The sign of the corresponding coefficient results in two scenarios, i.e., permanent or transitory behavior of sectoral CO_2. Thus, incorporating lagged-dependent sectoral CO_2 helps to capture inertia effects across IEA member countries (Wooldridge, 2016).

We further develop a comprehensive model that incorporates all sectoral-based fossil CO_2, green innovation, energy intensity, energy R&D, and industrial structure in GHG emissions function, expressed as:

$$\begin{aligned}\Delta lnGHG\ Emissions_{i,t} = {} & \delta_i + \lambda\Delta lnGHG\ Emissions_{i,t-1} \\ & + \gamma_1 Green\ Innovation_{i,t} \\ & + \gamma_2\Delta Energy\ Intensity_{i,t} + \gamma_3 lnEnergy\ R\&D_{i,t} \\ & + \gamma_4\Delta lnIndustrial\ Structure_{i,t} \\ & + \gamma_5\Delta lnBuildings_{i,t} + \gamma_6\Delta lnIndustry_{i,t} \\ & + \gamma_7\Delta lnOther_{i,t} + \gamma_8\Delta lnTransport_{i,t} \\ & + \gamma_9 lnPower_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{9}$$

Using the resultant parameters of individual sector-based fossil CO_2, we estimate observed and unobserved economic sectoral contributions to GHG emissions in IEA member countries using ranking. In this scenario, we can strictly assess the impact of disaggregate fossil CO_2 emissions on GHG emissions for policy purposes based on *ceteris paribus* assumption.

The green energy innovation model specification is constructed using the following expression:

$$\begin{aligned}Green\ Innovation_{i,t} = {} & \delta_i + \lambda Green\ Innovation_{i,t-1} \\ & + \gamma_1\Delta Energy\ Intensity_{i,t} + \gamma_2 lnEnergy\ R\&D_{i,t} \\ & + \gamma_3\Delta lnIndustrial\ Structure_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{10}$$

This model exclusively assesses the role of energy and its services and industrial structure in expanding green energy innovation amidst increasing level of energy intensity. The dynamic model specifications

Table 1
Assessment of fossil-based anthropogenic emissions.

	Δf	GHG		Buildings		Industry		Other		Transport		Power	
		(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
GHG_{t-1}	–	−0.063* [0.035]	−0.002** [0.001]	–	–	–	–	–	–	–	–	–	–
$Buildings_{t-1}$	–	–	–	−0.064 [0.045]	−0.056*** [0.025]	–	–	–	–	–	–	–	–
$Industry_{t-1}$	–	–	–	–	–	−0.095*** [0.040]	−0.059** [0.028]	–	–	–	–	–	–
$Other_{t-1}$	–	–	–	–	–	–	–	−0.064 [0.052]	−0.067** [0.032]	–	–	–	–
$Transport_{t-1}$	–	–	–	–	–	–	–	–	–	0.272*** [0.056]	0.204*** [0.030]	–	–
$Power_{t-1}$	–	–	–	–	–	–	–	–	–	–	–	0.944*** [0.016]	0.774*** [0.007]
GHG	−13.149***	–	–	0.620*** [0.181]	0.557*** [0.061]	0.760*** [0.164]	0.656*** [0.051]	0.654*** [0.155]	0.597*** [0.057]	0.364*** [0.066]	0.251*** [0.032]	1.861*** [0.239]	1.712*** [0.354]
Buildings	−13.703***	0.116** [0.018]	0.085*** [0.008]	–	–	–	–	–	–	–	–	–	–
Industry	−12.245***	0.154*** [0.028]	0.139*** [0.011]	–	–	–	–	–	–	–	–	–	–
Other	−12.909***	0.094*** [0.019]	0.080*** [0.011]	–	–	–	–	–	–	–	–	–	–
Transport	−9.864***	0.254*** [0.031]	0.129*** [0.017]	–	–	–	–	–	–	–	–	–	–
Power	−2.380[a]***	0.007** [0.003]	0.002*** [0.000]	–	–	–	–	–	–	–	–	–	–
Green energy innovation	−3.207[a]***	−0.001 [0.013]	−0.010* [0.006]	−0.028* [0.016]	0.024 [0.022]	0.005 [0.019]	−0.005 [0.019]	−0.012 [0.017]	0.009 [0.021]	−0.018* [0.011]	−0.036*** [0.011]	0.035 [0.043]	0.152 [0.123]
Energy intensity	−12.793***	2.231*** [0.580]	1.493*** [0.140]	4.002*** [1.375]	4.925*** [0.475]	0.277 [0.596]	0.227 [0.405]	−0.980* [0.533]	−1.868*** [0.450]	−0.622 [0.400]	−0.242 [0.237]	2.132 [1.681]	−2.366 [2.765]
Energy R&D	−3.178[a]***	−0.001 [0.002]	−0.001*** [0.000]	−0.002 [0.005]	0.001 [0.001]	−0.005** [0.002]	−0.001* [0.001]	−0.001 [0.004]	−0.001 [0.001]	−0.003 [0.005]	−0.001** [0.000]	−0.003 [0.006]	0.014** [0.006]
Industrial structure	−11.443***	−0.111 [0.069]	−0.132*** [0.046]	0.511*** [0.154]	0.541*** [0.158]	−0.222 [0.272]	−0.612** [0.135]	−0.755*** [0.164]	−0.609*** [0.153]	−0.015 [0.108]	−0.061 [0.081]	0.998* [0.577]	1.123 [0.914]
Convergence	–	Y	–	Y	–	Y	–	Y	–	Y	–	Y	–
Resample	–	CSD	–	CSD	–	CSD	–	CSD	–	CSD	–	CSD	–
Initialization	–	AHE	–	AHE	–	AHE	–	AHE	–	AHE	–	AHE	–
LM	–	244.1*	244.1*	454.9***	454.9***	226.5	226.5	273.7***	273.7***	359.5***	359.5***	1087***	1087***
LM^{b}_{adj}	–	2.354**	2.354**	35.89***	35.89***	0.867	0.867	8.187***	8.187***	21.33***	21.33***	133.4***	133.4***
LM^{b}_{CD}	–	1.244	1.244	5.061***	5.061***	4.589***	4.589***	4.892***	4.892***	9.048***	9.048***	20.31***	20.31***
Δ	–	7.733***	7.733***	7.903***	7.903***	4.204***	4.204***	4.087***	4.087***	6.669***	6.669***	14.281***	14.281***
Δ_{adj}	–	9.126***	9.126***	8.725***	8.725***	4.641***	4.641***	4.512***	4.512***	7.363***	7.363***	15.766***	15.766***
Cointegration	–	Y-K	Y-K	Y-K	Y-K	Y-K	Y-K	Y-K	Y-K	Y-K	Y-K	Y-W	Y-W
Countries	–	21	21	21	21	21	21	21	21	21	21	21	21
Obs	–	798	819	798	798	798	798	798	798	798	798	819	819
R^2	–	–	0.825	–	0.597	–	0.569	–	0.516	–	0.552	–	0.977

Notes: [a] level stationary series, [b] LM test based on two-sided biased-adjusted estimation test, Y-(K/W) validation of long-term relationship with Kao (K) and Westerlund (W) cointegration tests, CSD means cross-section dependence, AHE denotes analytical heterogeneous, LM, LM_{adj}, and LM_{CD} represent Breusch-Pagan LM, Biased-adjusted LM and CD tests. Δf represents rejection of the null hypothesis of unit root. **(1)** Estimated using cross-sectional time series biased-corrected fixed-effects; **(2)** Estimated using panel-kernel based regularized least-squares. *, **, *** signify statistical significance at 99, 95, 90% confidence interval.

expressed in Eqs. (4)–(10) are estimated with panel biased-corrected fixed-effects estimator using bootstrapping technique for estimation and statistical inferences. In Eqs. (4)–(9), we utilize the cross-sectional dependence scheme for resampling pattern of error terms and analytical heterogeneous method for generating the initialization conditions. In contrast, Eq. (10) applies four different resampling error schemes namely cross-sectional dependence, cross-sectional heteroskedasticity, wild bootstrap, and cross-sectional heteroskedasticity based on Monte Carlo error sampling. Similarly, Eq. (10) applies three methods for initialization conditions namely burn-in, analytical heterogeneous, and deterministic (De Vos et al., 2015; Everaert and Pozzi, 2007). The choice of optimal resampling scheme and initialization method depends largely on stationary properties, cross-section dependence, and heterogeneous characteristics of data series and model specification. For model specifications in Eqs. (4)–(10), we derive the corresponding standard errors using non-parametric bootstrap distribution of the dynamic panel estimator (Sarkodie and Owusu, 2020). The estimated models are validated using panel biased-corrected fixed-effects distribution of autoregressive coefficients expressed in histogram (Supplementary Figs. 1–7).

To improve the consistency of the estimated model, we mimic the econometric-based model specification with panel Kernel-based regularized least squares. This machine learning-based estimator eliminates linearity and controls for heterogeneity in lieu of misspecification bias, hence, produces consistent pointwise parameter estimates and marginal effects (Hainmueller and Hazlett, 2014). Contrary to the manual model specification using panel biased-corrected fixed-effects estimator, the Gaussian-kernel based regularized least-squares automatically selects an optimal functional form by learning the data dynamics. For brevity, the panel Kernel-based regularized least squares can be expressed in a generic form as:

$$f(I) = \sum_{i=1}^{N} c_i k(I, I_i), D = f(I) \tag{11}$$

where D is the target variable, I denotes the predictors, c_i represents the weight of the predictors, and $k(I, I_i)$ pulls similarity evidence from the observations. The estimator automatically selects an optimal kernel bandwidth and regularization parameter. Thus, the pointwise derivatives of the target variables ($\Delta lnBuildings_{i,\ t}$, $\Delta lnIndustry_{i,\ t}$, $\Delta lnOther_{i,\ t}$,

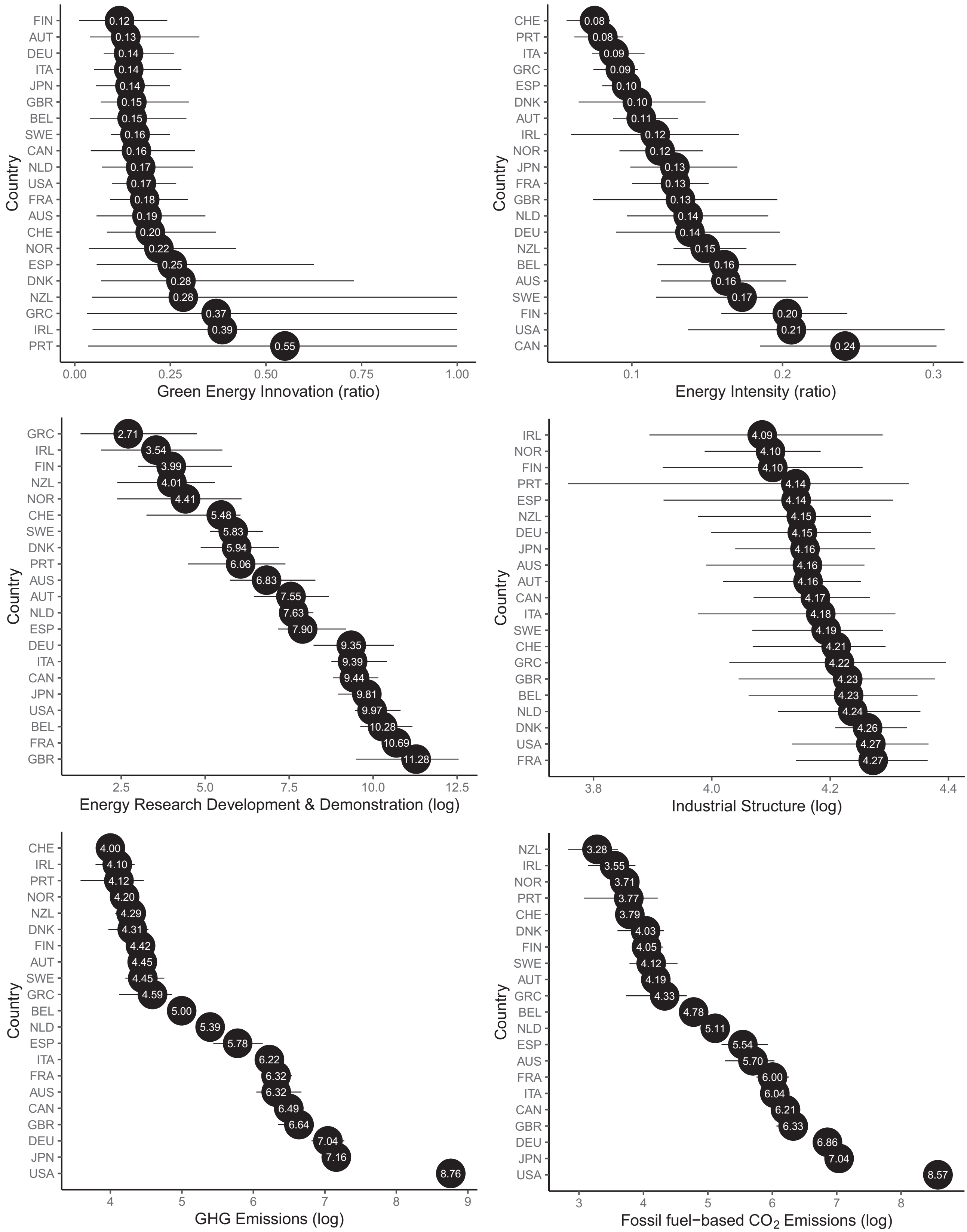

Fig. 1. 40-Year cross-country trend of (a) green energy innovation (b) energy intensity (c) energy research and development (d) industrial structure (e) GHG emissions (f) fossil fuel-based CO_2 emissions. The lollipop plot shows horizontal line from left to right––representing minimum and maximum whereas the black dot signifies the mean with overlayed text in descending order.

$\Delta lnTransport_{i,\ t}$, $lnPower_{i,\ t}$, and $\Delta lnGHG\ Emissions_{i,\ t}$) and predictors can be estimated to explore the pointwise marginal effects using the estimator expressed as (Hainmueller and Hazlett, 2014):

$$E_N\left[\frac{\widehat{\partial D}}{\partial I_j^{(d)}}\right] = \frac{-2}{\sigma^2 N}\sum_j \sum_i c_i e^{-\|I_i - I_j\|^2} k\left(I_i^{(d)} - I_j^{(d)}\right) \tag{12}$$

where $\frac{\widehat{\partial D}}{\partial I_j^{(d)}}$ is the partial derivative of the target variables to the predictors, σ^2 is kernel bandwidth.

The effect of regime-dependent fossil-based CO_2 emissions on green energy innovation is modeled using novel panel threshold fixed-effects expressed as (Wang, 2015):

$$\begin{aligned} Green\ Innovation_{i,t} = \mu + X_{i,t}\ (\delta_{i,t} < \gamma_1)^* \beta_1 + X_{i,t}\ (\gamma_1 \le \delta_{i,t} < \gamma_2)^* \beta_2 \\ + X_{i,t}\ (\delta_{i,t} \ge \gamma_2)^* \beta_3 + u_i + \varepsilon_{i,t} \end{aligned} \tag{13}$$

where u_i is country-specific effects, and $\varepsilon_{i,\ t}$ is white noise. $X_{i,\ t}$ denote covariates $\Delta Energy\ Intensity_{i,\ t}$, $lnEnergy\ R\ \&\ D_{i,\ t}$ and $\Delta lnIndustrial\ Structure_{i,\ t}$. $\delta_{i,\ t}$ and γ represent the threshold variable and parameter splitting of panel equation into three regimes with corresponding coefficients $\beta_1, \ldots, \beta_3$.

Finally, we re-estimate Eq. (9) using dynamic autoregressive distributed lag model with stochastic simulations expressed as (Jordan and Philips, 2018):

$$\begin{aligned} \Delta lnGHG\ Emissions_{i,t} = constant + \Delta lnGHG\ Emissions_{i,t-1} \\ + \gamma_1 Green\ Innovation_{i,t} \\ + \gamma_2 Green\ Innovation_{i,t-1} \\ + \gamma_3 \Delta Energy\ Intensity_{i,t} \\ + \gamma_4 \Delta Energy\ Intensity_{i,t-1} \\ + \gamma_5 lnEnergy\ R\&D_{i,t} + \gamma_6 lnEnergy\ R\&D_{i,t-1} \\ + \gamma_7 \Delta lnIndustrial\ Structure_{i,t} \\ + \gamma_8 \Delta lnIndustrial\ Structure_{i,t-1} \\ + \gamma_9 \Delta lnBuildings_{i,t} + \gamma_{10} \Delta lnBuildings_{i,t-1} \\ + \gamma_{11} \Delta lnIndustry_{i,t} + \gamma_{12} \Delta lnIndustry_{i,t-1} \\ + \gamma_{13} \Delta lnOther_{i,t} + \gamma_{14} \Delta lnOther_{i,t-1} \\ + \gamma_{15} \Delta lnTransport_{i,t} + \gamma_{16} \Delta lnTransport_{i,t-1} \\ + \gamma_{17} lnPower_{i,t} + \gamma_{18} lnPower_{i,t-2} + \varepsilon_{i,t} \end{aligned} \tag{14}$$

We use Eq. (14) to examine both long and short-term impacts of sectoral fossil-CO_2, green energy innovation, energy intensity, energy research and development, and industrial structure. The proposed estimator is used to stochastically simulate the long-term GHG effects of a counterfactual change in energy intensity from 2014 to 2064 based on *ceteris paribus* assumption. The 50-year prediction is essential to test the business-as-usual scenario where there is 1% increase in energy-intensive based economic development.

3. Results

3.1. Forty-year trend estimation in IEA member countries

The hotspot ranking of indicators identifies the minimum, mean and maximum activities of countries over 40 years. Using a lollipop plot presented in Fig. 1, we show that Finland and Portugal have the lowest (0.12) and highest (0.56) adoption level of green energy innovations, respectively. This implies that Portugal has more CO_2 abatement innovations compared to other IEA member countries. In connection with energy intensity, Switzerland records the lowest average (0.08) over 40 years whereas Canada ranks first (0.24). Higher energy intensity signifies lower energy efficiency due to higher level of energy utilization per GDP. Greece ranks 21st (2.71) in terms of contribution towards energy research development and demonstration whereas the UK ranks 1st (11.28). Both France and the US (4.27) have the largest industrial structure compared to Ireland (4.09). The US has the highest level of both fossil fuel-based CO_2 and GHG emissions whereas Switzerland and New Zealand have the lowest emissions (Fig. 1). We examine the annual change of over decadal sectoral-based fossil CO_2 using the compound annual growth rate formulation (Fig. 2). Using this expression enables easy comparison of persistent rate of reoccurrences of CO_2 across sectors of the same component. In this way, we can base our judgment on the business as usual scenario of the RCP 8.5 assuming sectoral-based fossil CO_2 grows at the same rate annually (van Vuuren et al., 2011). The sectoral-based fossil CO_2 includes Buildings, Industry, Other Sectors, Power Industry, and Transport. The highest compound annual growth rate of fossil CO_2 occurs in the power industry of Norway, New Zealand, Portugal, Australia, and Greece by 7.95%, 5.07%, 4.32%, 2.51%, and 2.45%, respectively. While GHG emissions declined in Norway, Australia, and Greece after 2009, historical high of GHG emissions is dominant from 1975 to 2009. Other sectors including agriculture, waste, indirect, and industrial activity emissions increased by 3.19%, 1.16%, 1.02%, 1.01%, and 0.72% compound annual growth rate in New Zealand, Australia, Canada, Netherlands, and Portugal. Top five hotspot countries like Greece, Ireland, Portugal, Australia, and Spain saw transport-based fossil CO_2 grow by 3.02%, 3.01%, 2.81%, 2.13%, and 2.11%, respectively. Buildings-based fossil CO_2 grew by 1.55%, 1.45% 1.17%, 0.59%, and 0.22% compound annual growth rate in Spain, Australia, Portugal, Ireland, and New Zealand. Besides, industry-based fossil CO_2 grew by 1.33%, 1.10%, 0.98%, 0.75%, and 0.36% in New Zealand, Norway, Canada, Australia, and Portugal. In contrast, Buildings-based fossil CO_2 saw the highest decline by 7.11%, 3.93%, 2.55%, 1.65%, and 1.37% compound annual growth rate in Sweden, Denmark, Finland, Germany, and Norway. Power industry-based fossil CO_2 dropped by 2.77%, 1.40%, 1.09%, 0.39%, and 0.17% in France, Belgium, the UK, Denmark, and Germany. Further assessment from historical data shows several EU countries saw a decline in GHG emissions from the power sector after the 2009 EU Renewables directive. Likewise, industry-based fossil CO_2 declined by 2.53%, 2.29%, 2.29%, 2.28%, and 2.24% in Sweden, France, the UK, Germany, and Italy, respectively. Other sector-based fossil CO_2 fell by 1.56%, 1.29%, 1.10%, 1.02%, and 0.98% in the UK, Italy, France, Norway, and Germany. It is important to note that transport is the only sector across IEA member countries that saw no decline (compound annual growth rate) in fossil CO_2 (see Fig. 2).

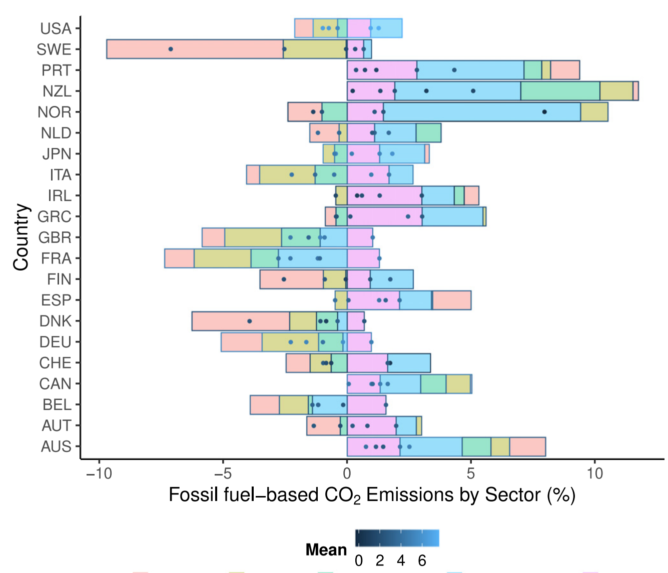

Fig. 2. Sectoral compound growth rate accounting of fossil-based CO_2 emissions. This figure shows the estimated compound annual growth rate (%) of sectoral-based fossil CO_2 on the x-axis and cross-countries on the y-axis. The filled bars denote sectoral growth rates and colored dots are 40-year mean across IEA member countries.

3.2. Convergence & heterogeneous causal effects

This theory posits that countries with similar economic structure converge over time (Quah, 1996). While convergence may hold in terms of economic productivity, it may fail in terms of environmental sustainability. Meanwhile, the environmental Kuznets curve theory postulates in part that higher-income countries become sophisticated with technology and environmental awareness, hence, decline emissions over time (Panayotou, 1993). The decline of emissions can be attributed to environmental policy stringency and a shift from carbon and energy-intensive economy to decarbonized and energy-efficient economic structure. Thus, high-income countries are expected to converge on anthropogenic emissions. To test this hypothesis, we first generate trend components of the data series using panel-based Hodrick-Prescott smoothing filter method (Hodrick and Prescott, 1997). This data filtering technique is necessary to estimate the long-term behavior of the indicators. We apply the proposed log-t regression test to examine the overall null hypothesis of convergence across countries (Phillips and Sul, 2007). Subsequently, we undertake sub-group formation into club membership and club merging for clubs satisfying

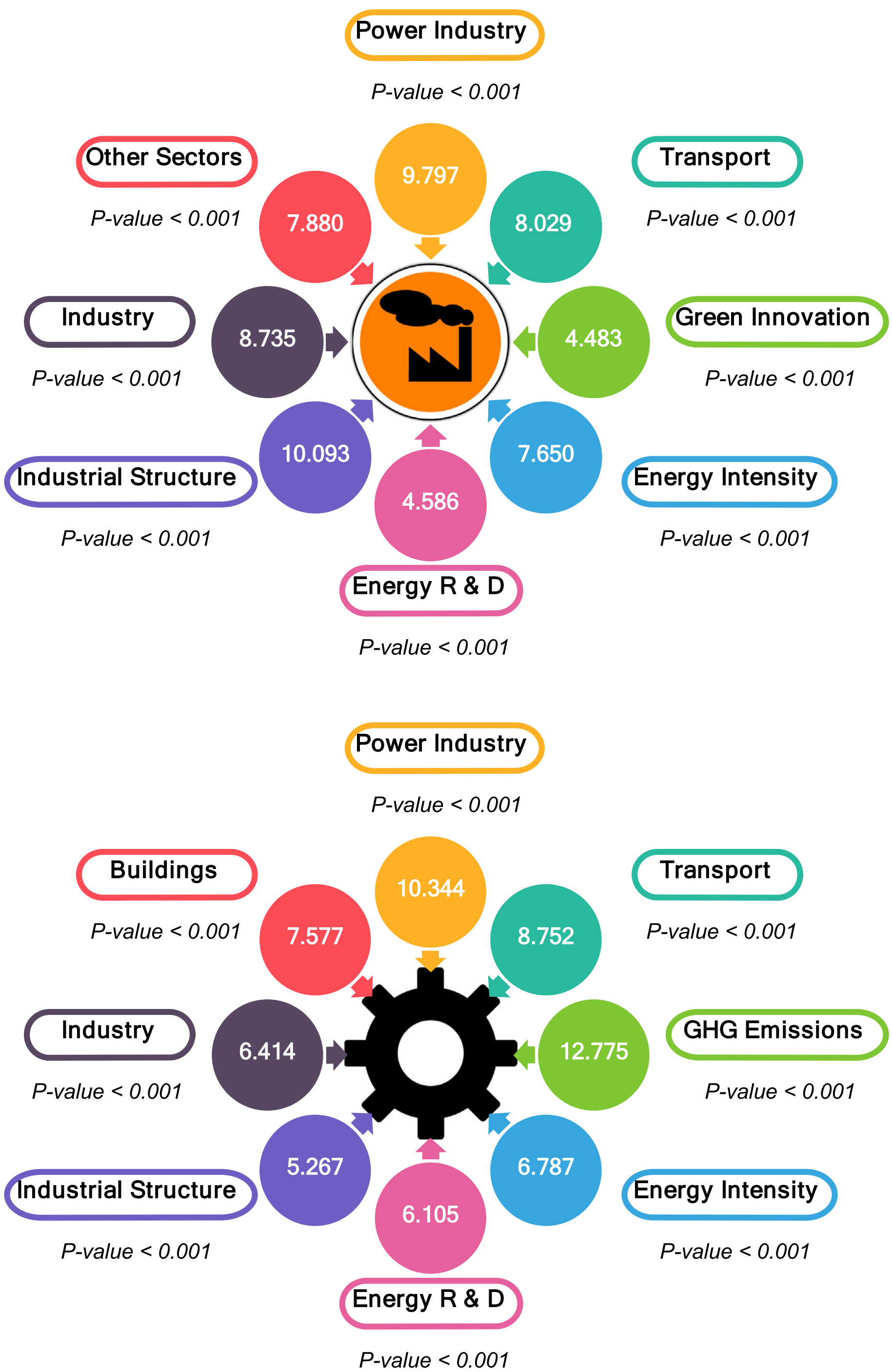

Fig. 3. Heterogeneous causal effect of (a) sectoral-based fossil-driven CO_2 and energy services on GHG emissions (b) sectoral-based anthropogenic emissions and energy services on green energy innovation. Estimated based on heterogeneous panel Granger non-causality test. The arrows depict the direction of causality whereas the *p-values* denote the rejection of the null hypothesis of non-causality.

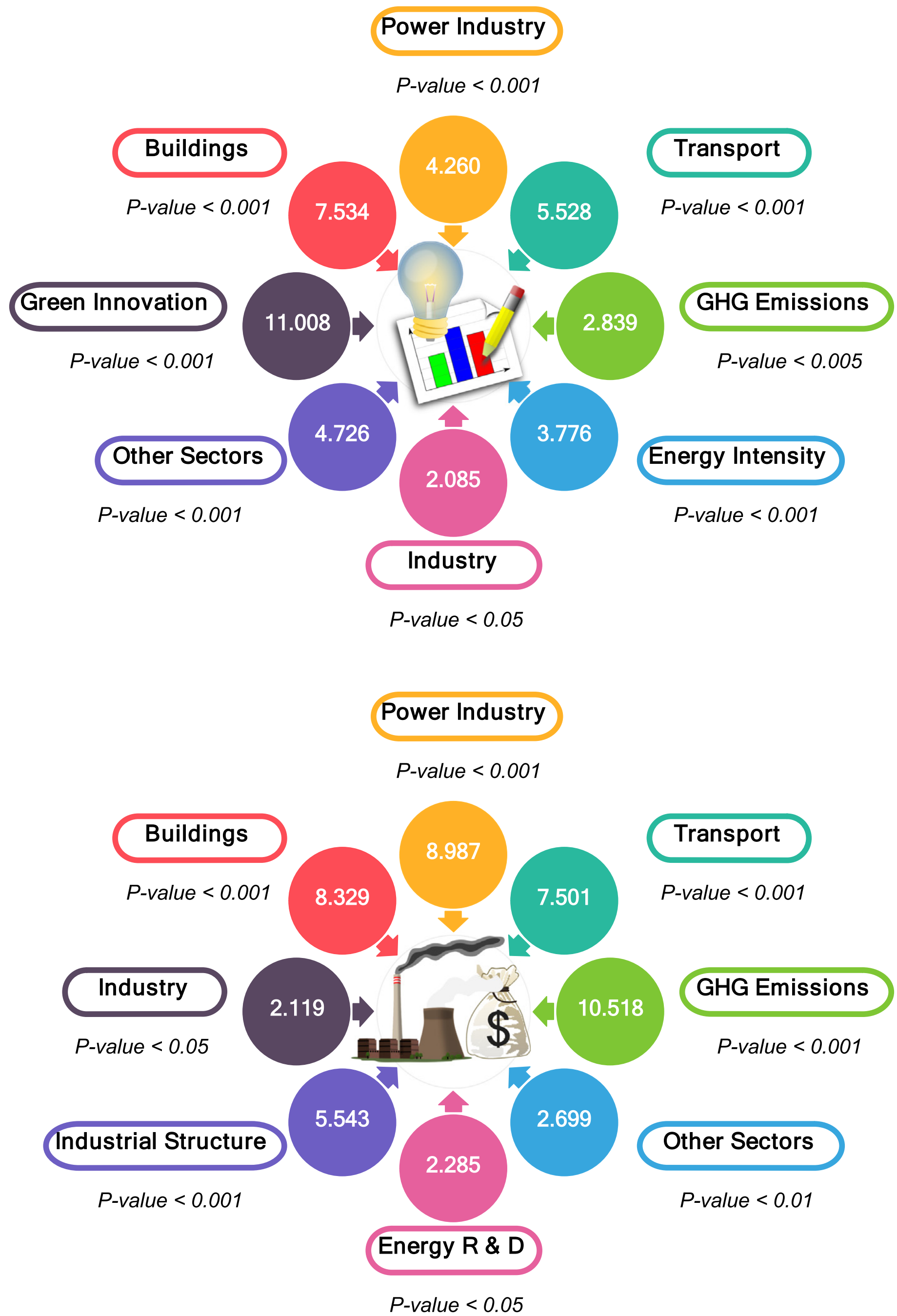

Fig. 4. Heterogeneous causal effect of (a) sectoral-based anthropogenic emissions and energy services on energy R&D (b) sectoral-based anthropogenic emissions and energy services on energy intensity. Estimated based on heterogeneous panel Granger non-causality test. The arrows depict the direction of causality whereas the *p-values* denote the rejection of the null hypothesis of non-causality.

the joint hypothesis of convergence (Du, 2017). We observe in Supplementary Table 1 that the overall log-*t*-test statistic for all data series is <-1.65 (i.e., rejecting $\boldsymbol{H_0}$: of convergence) except green energy innovation. This implies that industrialized high-income countries converge on green energy innovation but divergent on GHG emissions, energy intensity, energy R&D, industrial structure, and sectoral-based fossil CO_2. To examine heterogeneous effects across IEA member countries, we first examine both cross-section dependence (CD) and stationarity using Breusch-Pagan LM (LM), bias-adjusted LM (LM_{adj}), CD (LM_{CD}), and CADF tests. We observe from Table 1 column 2 that all data series are first-difference stationary except for power industry, green energy innovation, and energy R&D. Besides, we confirm the presence of panel correlation across countries for the proposed models, rejecting $\boldsymbol{H_0}$: of cross-section independence. This infers that IEA member countries are susceptible to global common shock including Covid-19 pandemic, oil shocks, market volatility, and spillover effects. Subsequently, we apply panel slope homogeneity test after validating the preconditions. In this test, we examine whether slope parameters are equal across countries (Pesaran and Yamagata, 2008). The estimated slope parameters (Δ, Δ_{adj}) reject $\boldsymbol{H_0}$: of identical slope coefficients at *p-value* < 0.01, confirming slope heterogeneity. Now, we estimate the panel heterogeneous causal effects as general-to-specific approach for our proposed model (Fig. 3). The panel heterogeneous Granger-causality is useful in assessing the predictive components of data series. We notice a rejection of the null hypothesis of no causality for all countries in Figs. 3–4. Thus, there is causality from transport, green energy innovation, energy intensity, energy R&D, industrial structure, industry, other sectors, and power industry to GHG emissions for at least one country (Fig. 3a). The country-specific causality shows that green energy innovation predicts GHG emissions in Belgium, Italy, Netherlands, Spain, and the US. Additionally, energy intensity predicts GHG emissions in Australia, Belgium, Canada, Denmark, Germany, Italy, Norway, and Spain. Besides, the power industry predicts GHG emissions in Australia, France, Germany, Greece, Ireland, Italy, New Zealand, Spain, and Switzerland (Supplementary Table 2). Similarly, we observe panel causality from transport, GHG emissions, energy intensity, energy R&D, industrial structure, industry, buildings, and power industry to green energy innovation (Fig. 3b). Besides, there is causality from transport, GHG emissions, energy intensity, industry, other sectors, green energy innovation, buildings, and power industry to energy research and development for at least one country (Fig. 4a). Likewise, causal relationship is observed from transport, GHG emissions, other sectors, energy R&D, industrial sector, industry, buildings, and power industry to energy intensity for at least one country (Fig. 4b). The country-pooled causality reveals that GHG emissions predict green energy innovation in Denmark, Finland, Netherlands, Norway, and Portugal. Energy R&D predicts green energy innovation in Denmark, Finland, Germany, Italy, Portugal, and Switzerland (Supplementary Table 4). The variations of empirical evidence across IEA member countries underpin our earlier findings of heterogeneous and divergence effect, highlighting the importance of using more sophisticated techniques to control these challenges.

3.3. Assessment of fossil-based anthropogenic emissions

We assess the drivers of GHG emissions and sectoral-based fossil CO_2 using both panel-bootstrap bias-corrected fixed-effects and panel-kernel regularized least-squares. While the former is our choice econometric approach for estimation, the latter technique based on machine learning is used to validate the parameter estimates. Using these sophisticated estimation techniques are useful to account for omitted-variable and misspecification bias, cross-section dependence, additivity, heterogeneity, and country-specific fixed-effects (Owusu and Sarkodie, 2020). The overall models show statistical significance at 1% level, with corresponding R^2 between 0.52 and 0.98 and residual independence (Supplementary Figs. 1–7). Thus, the regressors explain 52–98% of variations in anthropogenic emissions (Table 1). The GHG model shows a negative and significant GHG_{t-1}, signifying the recovery effect of historical GHG emissions. We find a positive and statistically significant parameter of sectoral-based fossil CO_2, implying that emissions

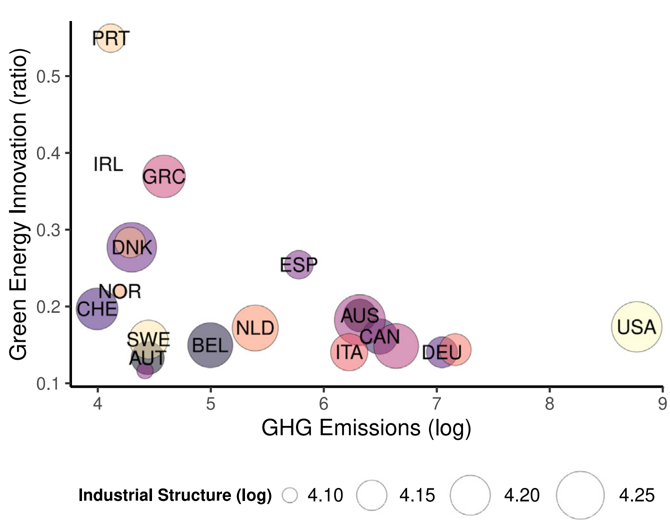

Fig. 5. Relationship between green energy innovation and GHG emissions while accounting for industrial structure.

from buildings, industry, other sectors (agriculture, waste, indirect emissions), transport, and power industry escalates GHG emissions in the long-term. Similarly, historical increase in energy intensity exacerbates GHG emissions by 1.49–2.23%. In contrast, improving green energy innovation, increasing energy research and development, and expanding industrial structure have mitigating effects on GHG emissions. To corroborate the findings, we examine the relationship between green energy innovation and GHG emissions while accounting for industrial structure. We observe in Fig. 5 that countries with high green energy innovation and medium-high industrial structure have lower GHG emissions and vice versa. For example, Portugal, Ireland, Greece, New Zealand, Denmark, Norway, and Switzerland have lower levels of GHG emissions whereas the US, Germany, Italy, Australia, and Canada with low-medium green energy innovation but high industrial structure emit more GHG. This implies that diversification of energy portfolio with green energy innovation has GHG emission-reduction effect. In the sectoral-based fossil CO_2 models, the coefficient on $Buildings_{t-1}$, $Industry_{t-1}$, and $Other_{t-1}$ is negative and significant––inferring that historical emission factors from buildings, industry and other sectors correct anomalies with time. Contrary, the parameter on $Transport_{t-1}$ and $Power_{t-1}$ are significantly positive with a large magnitude, especially power––implying that past emissions influence current levels of emissions from transport and power. Unobserved factors may explain the inertial effect of historical emissions from transport and power industry. Increasing levels (1%) of GHG emissions––the main cause of climate change––increase fossil CO_2 emissions from buildings (0.56–0.62%), industry (0.66–0.76%), other sectors (0.60–0.65%), transport (0.25–0.36%), and power industry (1.71–1.86%). Growth in energy intensity by 1% spur CO_2 emissions by 4.0–4.93% from buildings but declines other sector-based fossil CO_2 emissions by 0.98–1.87%. Expansion of industrial structure by 1% increases buildings-based fossil CO_2 emissions by 0.51–0.54% but declines industry and other sector-based fossil CO_2 emissions by 0.61% and 0.61–0.76%. Improving energy research and development by 1% decreases industry and transport-based fossil CO_2 emissions. Besides, accelerating green energy innovation declines long-term buildings and transport-based fossil CO_2 emissions. In summary, the impact of long-term economic sectoral-based fossil CO_2 on GHG emissions depicted in Fig. 6 can be expressed as –– transport > industry > buildings > others > power. Empirically, power, and heat generation contribute 0.46–1.12% of GHG emissions. Other sectors including agriculture, waste, and indirect emissions contribute 15.04–18.39% of GHG emissions. The building sector is ranked third contributor of long-term GHG emissions by 18.56–19.54%. The industrial sector including manufacturing and fuel production is ranked 2nd determinant of GHG emissions, contributing about 24.64–31.95%. Transportation is identified as the main contributor to long-term GHG emissions in a fossil-based CO_2 regime, contributing about 29.66–40.64%. This corroborates our earlier findings of persistent transport-based fossil CO_2 emissions across all countries depicted in Fig. 2. We examine the counterfactual change in GHG emissions from 2014 to 2064 using dynamic ARDL stochastic simulations. Using the business-as-usual scenario of the RCP 8.5, we assume energy intensity will grow at the same rate (1%) annually based on the compound annual growth rate estimation. We observe in Fig. 7 that 1% shock in energy intensity will increase GHG emissions by over 5.56% in 2064.

3.4. Regime-based fossil CO_2 effects on green energy innovation

We used panel-bootstrap bias-corrected fixed-effects to estimate Models 1–6 whereas Model 7 is estimated with panel threshold fixed-effects. The lagged-green energy innovation (λ) is positive and significant for all six models (Models 1–6) in Table 2. This suggests that countries with historical green energy orientation may invest ~58% more in achieving green growth through green innovation. Countries that have improved historical green energy innovation include Portugal, Ireland, Greece, New Zealand, Denmark, and Spain (Fig. 1a).

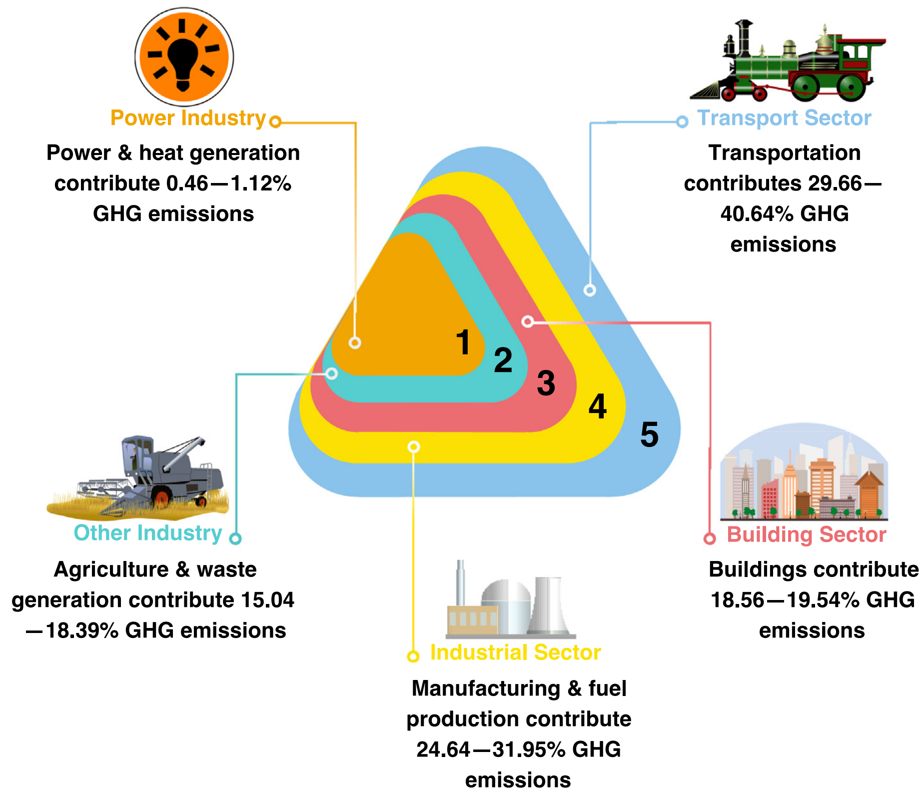

Fig. 6. Long-term contribution of sectoral-based fossil CO_2 to GHG emissions. Percentages calculated from the estimated parameters based on ceteris paribus assumption––using both panel-based kernel regularized least-squares and panel bootstrap bias-correction fixed-effects. The numbering system ranks sectoral-fossil CO_2 from lowest to highest.

This perhaps corroborates the findings in Table 1, explaining why countries with high investment in green energy innovation have low levels of GHG emissions (Fig. 5). Comparably, 1% investment increase in energy research and development expands green energy innovation by 0.01–0.02%. Investment in energy research and development across industrialized high-income countries may shift towards other energy technologies that expand economic productivity with limited green energy innovation. This may justify why techno-economic giants like the UK, France, Belgium, the US, Japan, Canada, Italy, and Germany have huge investments for energy research development and demonstration but limited green energy innovation (Fig. 1c). In contrast, 1% growth in

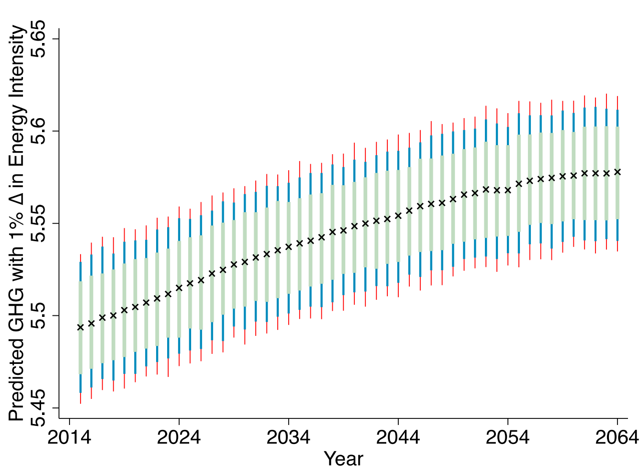

Fig. 7. Counterfactual change in GHG emissions with 1% Δ in energy intensity (%). The forecasting is executed based on the dynamic ARDL stochastic simulations. Olive teal, light blue and red spikes denote 75, 90, 95% confidence interval.

energy intensity and industrial structure expansion decline green energy innovation by ~0.78% and ~ 0.25%, respectively. In model 7, we validate the green energy innovation model by incorporating fossil CO_2 emissions as regime-dependent variable and GHG emissions as the threshold variable. The model specification is useful in assessing multiple thresholds of GHG emissions––exogeneous indicator of green energy innovation in a fossil regime. Evidence from model 7 validates the estimated parameters of energy intensity, energy R&D, and industrial structure. We observe that fossil CO_2 emissions from IEA member countries with very low and low-medium GHG emissions are significant and negatively related to green energy innovation. Contrary, fossil CO_2 emissions from IEA member countries with high GHG emission levels have positive relationship with green energy innovation. Thus, strengthening the theory of divergent GHG emissions across industrialized high-income countries. This implies the likelihood of IEA countries with lower economic productivity expanding their fossil-driven industrial structure by lowering green energy innovation standards. In contrast, higher GHG emission countries like the US may perhaps improve green energy innovation towards environmental sustainability.

4. Discussion

This study investigates the impact of energy intensity and economic-sectoral-based fossil CO_2 emissions including buildings, industry, transport, power, and other sectors spanning 1975–2014 across 21 IEA member countries. We caution that unobserved factors may affect GHG emissions and green energy innovations not addressed in this research, however, our empirical assessment is robust to estimation and misspecification bias. We further explore GHG mitigation effects of green energy innovation, energy research development and demonstration, and industrial structure. While existing literature largely focuses on the immediate drivers of aggregate anthropogenic emissions (Feng et al., 2015; Liang et al., 2016; Rosa and Dietz, 2012), this research examines both aggregate and disaggregate sectoral emissions, immediate

Table 2
Effect of regime-dependent fossil-based CO_2 emissions on green energy innovation.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
λ	0.574*** (0.433–0.707) [0.072]	0.576*** (0.419–0.735) [0.079]	0.577*** (0.447–0.692) [0.064]	0.564*** (0.428–0.729) [0.070]	0.566*** (0.437–0.696) [0.067]	0.566*** (0.434–0.666) [0.064]	–
Energy intensity	−0.741** (−1.727 to −0.246) [0.368]	−0.734** (−1.672 to −0.141) [0.360]	−0.761** (−1.464 to −0.115) [0.341]	−0.755** (−1.378 to −0.164) [0.326]	−0.776** (−1.433 to −0.231) [0.329]	−0.772** (−1.587 to −0.245) [0.362]	−1.534*** (−1.961 to −1.117) [0.215]
Energy R&D	0.014* (0.002–0.030) [0.008]	0.014* (0.000–0.030) [0.007]	0.013* (0.001–0.031) [0.007]	0.014* (0.002–0.033) [0.008]	0.015* (0.001–0.037) [0.009]	0.014* (0.002–0.034) [0.008]	0.037*** (0.024–0.051) [0.007]
Industrial structure	−0.233** (−0.477 to −0.025) [0.118]	−0.236** (−0.442 to −0.025) [0.113]	−0.242** (−0.420 to −0.037) [0.110]	−0.240** (−0.488 to −0.012) [0.116]	−0.248** (−0.435 to −0.053) [0.106]	−0.250** (−0.442 to −0.042) [0.119]	−0.527*** (−0.645 to −0.410) [0.060]
Constant	–	–	–	–	–	–	2.320*** (1.754–2.887) [0.289]
Regime#Fossil							
Very low	–	–	–	–	–	–	−0.528*** (−0.833 to −0.222) [0.156]
Low-medium	–	–	–	–	–	–	−9.552*** (−15.226 to −3.878) [2.891]
High	–	–	–	–	–	–	0.297** (−0.002–0.596) [0.152]
Threshold							
Single	–	–	–	–	–	–	13.430**
Double	–	–	–	–	–	–	8.640*
Triple	–	–	–	–	–	–	7.830
R-sq(within)	–	–	–	–	–	–	0.190
Observations	819	819	819	819	819	819	819
No. of countries	21	21	21	21	21	21	21
Resampling	CSD	WBOOT	CSD	CSHET	MCHE	MCHE	–
Initialization	Burn-in	AHE	AHE	Burn-in	AHE	DET	–
Convergence	Yes	Yes	Yes	Yes	Yes	Yes	–

Notes: λ is the lagged-dependent variable (green energy innovation); *,**,*** represents statistical significance at 10, 5 and 1% level; CSD denotes cross-section dependence; WBOOT denotes wild bootstrap, AHE denotes analytical heterogeneous; CSHET denotes cross-section heteroscedastic; MCHE denotes Monte Carlo heterogeneous; DET denotes deterministic; (..) represents 95% conf. interval; [..] is the standard error. LM (819.3, *p-value* < 0.01), LM_{adj} (96.85, *p-value* < 0.01), LM_{CD} (19.07, *p-value* < 0.01), Δ (19.343, *p-value* < 0.01), and Δ_{adj} (20.679, *p-value* < 0.01).

and underlying drivers, and policy measures useful for policy formulation. Our study shows that IEA member countries converge on green energy innovation––accentuating the potential of achieving clean energy through green growth. Contrary, achieving environmental sustainability through emission reduction, energy efficiency, energy R&D, and service-driven industrial structure remain divergent. This implies that country-specific policies on environmental sustainability will yield better results for mitigating anthropogenic emissions. Second, green energy innovation and energy R &D decline long-term GHG emissions by reducing negative environmental externalities. Investment and integration of energy R&D are reported to increase clean energy transition through sustainable electricity supply that is cost-effective and low in CO_2 emissions (Kittner et al., 2017). Additionally, green energy innovation hampers CO_2 emissions from buildings, implying that a transition towards green buildings improves both indoor and outdoor emissions (Nykamp, 2017). The variability in climatic patterns affects heating and cooling degree days, hence, affecting energy demand. If the energy requirement for these seasons is replaced with green energy technologies, energy consumption declines while reducing energy cost and indoor pollution (Castleton et al., 2010). We find that transport sector is the most persistent source of over-decadal CO_2 emissions––contributing about 29.66–40.64% of GHG emissions across IEA member countries. However, replacing fossils in the transport sector with green energy innovation-based alternative energy declines emissions by reducing transport footprint (van Vuuren et al., 2018). Besides, we find that fossil emissions increase green energy innovations in countries with high GHG emissions. This infers that IEA member countries in a fossil-based CO_2 regime are more likely to invest and adopt green energy innovations and pursue environmental sustainability after achieving economic prosperity. Increasing investment in energy research development and demonstration is critical for green energy innovations and facilitates the transition towards clean energy and emission reduction.

5. Conclusion

Reducing climate change and its related impacts remain critical to achieving environmental sustainability. However, growing population demand for energy and sustained economic productivity appears a hurdle for the mitigation target. While the extant literature has explored the determinants of anthropogenic GHG emissions, studies on the role of policy drivers including green energy innovation and energy research and development are limited. These green growth drivers act as abatement strategies of global emissions in carbonized and energy-intensive economies. To advance global and policy discussions, we examined how fossil emissions appear advantageous to green energy innovations, and energy R&D across industrialized high-income IEA countries.

The forty-year trend estimation showed power sector-driven GHG emissions declined substantially after 2009, coinciding with the 2009 renewables directive (Directive 2009/28/EC) by the EU. This perhaps prompted several EU member countries to develop national goals for renewables––that declined the share of fossil fuels in the energy portfolio––leading to a decline in GHG emissions. The incorporation of green energy innovation amidst sectoral emissions showed 1% increase in energy intensity could spur GHG emissions from 5.47% in 2014 to over 5.56% in 2064. While there is potential increase in GHG emissions from 2014 to 2064, the rate of increase is relatively low. This infers green energy innovation is useful in energy diversification and decarbonization of economic productivity. Besides, we observed low concentration of GHG emissions from IEA countries including, inter alia, Portugal, Denmark, Sweden, Norway, Switzerland, and Austria–– with high adoption of green energy innovation. Our empirical results support the European Green Deal agenda––of reducing emissions and preserving environmental quality through investment and adoption of green energy innovation. However, while our analysis showed evidence of convergence in green energy innovations, IEA member countries appear to diverge in GHG emissions. While IEA member countries are industrialized and developed economies, their economic structure and composition are different, hence, similar emission targets may hamper sustained economic development. This implies caution in the integration of green energy innovation in high carbonized economies––to avoid potential tradeoff between sustained economic growth, and environmental sustainability. Nevertheless, our study showed green growth strategies are useful in achieving decarbonized and energy-efficient growth while mitigating emissions.

Because of limitation in acquiring extensive data for the sampled series, our data periodicity spans from 1975 to 2014––thus, this implies our data capture exactly 2 years after the inception of the sustainable development goals (SDGs). Future research could adopt dataset that captures more years of the SDGs and several income groups––to assess the effect and limitations of income status on green energy innovation and green growth.

Data availability

Data utilized in this study are available on public repositories and can be acquired from IEA, OECD, World Bank, and EDGAR databases.

CRediT authorship contribution statement

Samuel Asumadu Sarkodie: Conceptualization, Formal analysis, Funding acquisition, Methodology, Software, Validation, Visualization, Writing – review & editing. **Phebe Asantewaa Owusu:** Writing – original draft, 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.

Acknowledgment

Open access funding provided by Nord University, Bodø, Norway.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.147257.

References

Bowman, D.M.J.S., Kolden, C.A., Abatzoglou, J.T., Johnston, F.H., van der Werf, G.R., Flannigan, M., 2020. Vegetation fires in the Anthropocene. Nat. Rev. Earth Environ. 1 (10), 500–515. https://doi.org/10.1038/s43017-020-0085-3.
Bronselaer, B., Zanna, L., 2020. Heat and carbon coupling reveals ocean warming due to circulation changes. Nature 584 (7820), 227–233. https://doi.org/10.1038/s41586-020-2573-5.
Castleton, H.F., Stovin, V., Beck, S.B.M., Davison, J.B., 2010. Green roofs; building energy savings and the potential for retrofit. Energy Build. 42 (10), 1582–1591. https://doi.org/10.1016/j.enbuild.2010.05.004.
Chakraborty, S.K., Mazzanti, M., 2020. Energy intensity and green energy innovation: checking heterogeneous country effects in the OECD. Struct. Chang. Econ. Dyn. 52, 328–343.
Chan, E., 2009. Harvard Business School Confidential: Secrets of Success. John Wiley & Sons.
Crippa, M., Oreggioni, G., Guizzardi, D., Muntean, M., Schaaf, E., Lo Vullo, E., ... Vignati, E., 2019. Fossil CO2 and GHG Emissions of All World Countries. Publication Office of the European Union, Luxemburg.
D'Alessandro, S., Cieplinski, A., Distefano, T., Dittmer, K., 2020. Feasible alternatives to green growth. Nat. Sustain. 3 (4), 329–335. https://doi.org/10.1038/s41893-020-0484-y.
De Vos, I., Everaert, G., Ruyssen, I., 2015. Bootstrap-based bias correction and inference for dynamic panels with fixed effects. Stata J. 15 (4), 986–1018.
Ditzen, J., Bersvendsen, T., 2020. xthst: testing for slope homogeneity in Stata. Paper Presented at the London Stata Conference 2020.
Du, K., 2017. Econometric convergence test and club clustering using Stata. Stata J. 17 (4), 882–900.
Dumitrescu, E.-I., Hurlin, C., 2012. Testing for Granger non-causality in heterogeneous panels. Econ. Model. 29 (4), 1450–1460.
Everaert, G., Pozzi, L., 2007. Bootstrap-based bias correction for dynamic panels. J. Econ. Dyn. Control. 31 (4), 1160–1184.
Feng, K., Davis, S.J., Sun, L., Hubacek, K., 2015. Drivers of the US CO2 emissions 1997–2013. Nat. Commun. 6 (1), 7714. https://doi.org/10.1038/ncomms8714.
Fujimori, S., Hasegawa, T., Krey, V., Riahi, K., Bertram, C., Bodirsky, B.L., ... van Vuuren, D., 2019. A multi-model assessment of food security implications of climate change mitigation. Nat. Sustain. 2 (5), 386–396. https://doi.org/10.1038/s41893-019-0286-2.
Hainmueller, J., Hazlett, C., 2014. Kernel regularized least squares: reducing misspecification bias with a flexible and interpretable machine learning approach. Polit. Anal. 22 (2), 143–168.
Hodrick, R.J., Prescott, E.C., 1997. Postwar US business cycles: an empirical investigation. J. Money, Credit, Bank. 1–16.
IEA, 2020. Clean Energy Innovation. Retrieved from. https://www.iea.org/reports/clean-energy-innovation.
Jordan, S., Philips, A.Q., 2018. Cointegration testing and dynamic simulations of autoregressive distributed lag models. Stata J. 18 (4), 902–923 Retrieved from. http://www.stata-journal.com/article.html?article=st0545.
Kittner, N., Lill, F., Kammen, D.M., 2017. Energy storage deployment and innovation for the clean energy transition. Nat. Energy 2 (9), 17125. https://doi.org/10.1038/nenergy.2017.125.
Le Quéré, C., Korsbakken, J.I., Wilson, C., Tosun, J., Andrew, R., Andres, R.J., ... van Vuuren, D.P., 2019. Drivers of declining CO2 emissions in 18 developed economies. Nat. Clim. Chang. 9 (3), 213–217. https://doi.org/10.1038/s41558-019-0419-7.
Liang, S., Wang, H., Qu, S., Feng, T., Guan, D., Fang, H., Xu, M., 2016. Socioeconomic drivers of greenhouse gas emissions in the United States. Environ. Sci. Technol. 50 (14), 7535–7545. https://doi.org/10.1021/acs.est.6b00872.
Meckling, J., Allan, B.B., 2020. The evolution of ideas in global climate policy. Nat. Clim. Chang. 10 (5), 434–438. https://doi.org/10.1038/s41558-020-0739-7.
Meckling, J., Sterner, T., Wagner, G., 2017. Policy sequencing toward decarbonization. Nat. Energy 2 (12), 918–922. https://doi.org/10.1038/s41560-017-0025-8.
Meehl, G.A., Stocker, T.F., Collins, W.D., Friedlingstein, P., Gaye, A.T., Gregory, J.M., ... Noda, A., 2007. Global climate projections. Climate change 2007: the physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.
Meng, F., Xu, Y., Zhao, G., 2020. Environmental regulations, green innovation and intelligent upgrading of manufacturing enterprises: evidence from China. Sci. Rep. 10 (1), 14485. https://doi.org/10.1038/s41598-020-71423-x.
Nykamp, H., 2017. A transition to green buildings in Norway. Environ. Innov. Soc. Transit. 24, 83–93. https://doi.org/10.1016/j.eist.2016.10.006.
Owusu, P.A., Sarkodie, S.A., 2020. Global estimation of mortality, disability-adjusted life years and welfare cost from exposure to ambient air pollution. Sci. Total Environ. 742, 140636. https://doi.org/10.1016/j.scitotenv.2020.140636.
Panayotou, Theodore. Empirical tests and policy analysis of environmental degradation at different stages of economic development. No. 992927783402676. International Labour Organization, 1993.
Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econ. 22 (2), 265–312.
Pesaran, M.H., Yamagata, T., 2008. Testing slope homogeneity in large panels. J. Econ. 142 (1), 50–93.
Pesaran, M.H., Ullah, A., Yamagata, T., 2008. A bias-adjusted LM test of error cross-section independence. Econ. J. 11 (1), 105–127.
Phillips, P.C., Sul, D., 2007. Transition modeling and econometric convergence tests. Econometrica 75 (6), 1771–1855.
Popp, D., Hascic, I., Medhi, N., 2011. Technology and the diffusion of renewable energy. Energy Econ. 33 (4), 648–662. https://doi.org/10.1016/j.eneco.2010.08.007.
Quah, D.T., 1996. Twin peaks: growth and convergence in models of distribution dynamics. Econ. J. 106 (437), 1045–1055.
Rockström, J., Gaffney, O., Rogelj, J., Meinshausen, M., Nakicenovic, N., Schellnhuber, H.J., 2017. A roadmap for rapid decarbonization. Science 355 (6331), 1269. https://doi.org/10.1126/science.aah3443.

Rosa, E.A., Dietz, T., 2012. Human drivers of national greenhouse-gas emissions. Nat. Clim. Chang. 2 (8), 581–586.
Sarkodie, S.A., Owusu, P.A., 2020. How to apply dynamic panel bootstrap-corrected fixed-effects (xtbcfe) and heterogeneous dynamics (panelhetero). MethodsX 7, 101045.
Sarkodie, Samuel Asumadu, Owusu, Phebe Asantewaa, 2021. Global effect of city-to-city air pollution, health conditions, climatic & socio-economic factors on COVID-19 pandemic. Sci. Total Environ. 778 (15 July 2021), 146394. https://doi.org/10.1016/j.scitotenv.2021.146394.
Sarkodie, S.A., Strezov, V., 2019. A review on Environmental Kuznets Curve hypothesis using bibliometric and meta-analysis. Sci. Total Environ. 649, 128–145. https://doi.org/10.1016/j.scitotenv.2018.08.276.
Sarkodie, S.A., Ajmi, A.N., Adedoyin, F.F., Owusu, P.A., 2021. Econometrics of anthropogenic emissions, green energy-based innovations, and energy intensity across OECD countries. Sustainability 13 (8), 4118 Retrieved from. https://www.mdpi.com/2071-1050/13/8/4118.
Schmidt, T.S., Sewerin, S., 2017. Technology as a driver of climate and energy politics. Nat. Energy 2 (6), 1–3.
Trnka, M., Rötter, R.P., Ruiz-Ramos, M., Kersebaum, K.C., Olesen, J.E., Žalud, Z., Semenov, M.A., 2014. Adverse weather conditions for European wheat production will become more frequent with climate change. Nat. Clim. Chang. 4 (7), 637–643. https://doi.org/10.1038/nclimate2242.
van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., ... Rose, S.K., 2011. The representative concentration pathways: an overview. Clim. Chang. 109 (1), 5. https://doi.org/10.1007/s10584-011-0148-z.
van Vuuren, D.P., Stehfest, E., Gernaat, D.E.H.J., van den Berg, M., Bijl, D.L., de Boer, H.S., ... van Sluisveld, M.A.E., 2018. Alternative pathways to the 1.5 °C target reduce the need for negative emission technologies. Nat. Clim. Chang. 8 (5), 391–397. https://doi.org/10.1038/s41558-018-0119-8.
Wang, Q., 2015. Fixed-effect panel threshold model using Stata. Stata J. 15 (1), 121–134.
Wilson, C., Grubler, A., Gallagher, K.S., Nemet, G.F., 2012. Marginalization of end-use technologies in energy innovation for climate protection. Nat. Clim. Chang. 2 (11), 780–788. https://doi.org/10.1038/nclimate1576.
Wooldridge, J.M., 2016. Introductory Econometrics: A Modern Approach. Nelson Education.