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Econometrics of Anthropogenic Emissions, Green Energy-Based Innovations, and Energy Intensity across OECD Countries

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Abstract: The increasing global attention on climate change underscores the importance of alternative energy technologies with emission reduction effects. However, there are several caveats of economic productivity and environmental sustainability tradeoffs that require empirical consideration—owing to long-term effects on climate change. Here, we examine the relationship between emissions, green energy-based innovations, and energy research and development across energy-intensive OECD countries while accounting for industrial structure dynamics. We utilize several novel time series and panel estimation techniques including time-varying causality, defactored instrumental variable-based homogeneous, and heterogeneous slope dynamics that control for unobserved common factors. Our empirical assessment emphasizes the significance of energy research and development in expanding green energy innovations while reducing long-term emissions. Conversely, continual dependence on obsolete energy research and development may worsen environmental sustainability. However, the inclusion of green energy technologies offset environmental pollution without compromising economic productivity. Besides, the mitigation effect of energy research and development is channeled through a decline in energy intensity and technological advancement. We show that green energy-based innovations and energy research and development play a critical role in achieving environmental sustainability in OECD countries.



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Keywords: time-varying causality; green energy innovations; instrumental variables; xtivdfreg; research and development; green growth

1. Introduction

Reducing biodiversity, declining global food production, rising sea levels, and higher morbidity rates are examples of the possible problems associated with global warming [1,2]. In recent years, the transition from carbon-intensive driven economic development to low-carbon economy has been examined through the lens of clean and renewable energy and improvement in energy efficiency [1,3,4]. Energy acts as a double-edged sword by serving as a vital condiment of economic growth and development—whereas driving environmental degradation [4]. As a result of the triple-headed scourge of climate change, resource depletion, and environmental degradation, green industries are on the rise [5]. Green industries are industries that adopt green innovation in production processes. Accordingly, green innovation connotes a series of introduced practices, techniques, technologies, and systems as well as products resulting from reduced environmental degradation [6]. Green innovation is reported to play a major part in energy development, especially in the industrial sector. The number of technological innovations is roughly measured using green patents issued in the region. Patents are momentous gauge of innovations in a

country, thus, those issued on reducing energy consumption and environmental concerns are regarded as green patents [3].

However, energy utilization is part of the production process with long-term effects on environmental quality—if the composition of fossil fuels is dominant in the energy portfolio. The realization of high carbon is due to limited clean technologies, high consumption of fossil fuels, and industrial development [7]. This phenomenon is perfectly encapsulated by China's primary energy annual growth rate use of about 3.9% in contrast with the world's figure of 1.5%, making them the world's largest energy consumer [7,8]. Hence, the laws implemented in China to stimulate sustainable development include Environmental Protection Law (revised in 2014) and Urban Greening Ordinance (revised in 2017) [9]. Therefore, reducing energy consumption and seeking ways to shrink the amount of energy used per unit of input are vital strategies in reducing carbon emissions [3,9]. It is reported that energy intensity in heavily industrialized OECD nations has plummeted by four times between 1970–2005. Energy used per unit of input is classified as high if more energy is used in the production of one unit of output [7]. Consequently, 1% rise in green patenting activities leads to 0.03% decline in energy intensity. Against this backdrop, research and development, technological acquisition, and a rise in technological innovations are reported to reduce energy intensity [3].

Energy structure and utilization have morphed in recent times, with green energy coming to the fore globally. Revamping the energy sector across countries is rife, chiefly due to adverse effects of conventional energy forms. Environmental degradation in the form of climate change due to global warming has heightened research into green energy. Energy research development has manifested in green restructuring and environmental regulation [6,10]. This is explained by the greening of industries and environmental protection allied with sustainable development. The greening of existing industries refers to the transformation of existing manufacturing sectors to create products in more environmentally friendly ways [5]. Paradigm shifts in industrial structure hinge on the composition, production, and consumption of energy. Energy research development and demonstration have manifested in four major forms namely path creation, path renewal, path diversification, and path importation. Path creation is the rise of totally new green industries whereas path renewal connotes the adoption of green innovations in established sectors. In contrast, path diversification refers to a spillover of knowledge and expertise from existing green industry to emerging green industry whereas path importation is the settlement of green industries new to a region as a result of inflows of expertise [5,11]. These techniques are paramount especially across heavily industrialized countries in Europe. Among these include the greening of metallurgical and chemical processes in Agder, Norway—where Eyde Zero-Waste initiative and Eyde Biocarbon program were carried out. The former focused on the transformation of waste into useful raw material, while the latter dealt with replacing fossils, viz. coal, used in the smelting industry with biocoal gleaned from Norwegian forests. Germany is in the process to adopt path diversification to its offshore wind power industry [5]. These countries are equipped with modern industrial structures to accommodate the reforms.

Despite these great strides in energy restructuring and development, a burgeoning and efficient industrial sector can act as a double-edged sword by either fostering or hindering green paths by resisting change and protecting past investments. Although development plans in recent years have had more energy-related goals across OECD countries, signifying the burgeoning appeal of cleaner energy sources. However, technological obsolescence and other existing factors may hamper the improvements in green energy innovations. Thus, this study investigates current progress of green energy innovations and effects on historical emissions while controlling for energy research and development, industrial structure, and energy intensity. We strategically adopt OECD countries with carbon and energy-intensive economies and interest in environmental sustainability through the adoption of alternative energy technologies.

Given the foregoing, this study contributes to the ongoing debate on green innovation and climate change by the implementation of novel time-varying Granger causality test based on recursive evolving algorithm. This test represents a new version of time-varying causality in existing literature that can detect real-time instability in relationships between variables, variations in causal direction, and periods of economic turbulence. Besides, this methodology incorporates consistent econometric techniques for integration and cointegration of sampled series. Besides, no prior knowledge of unit root properties is required. Second, we introduce the novel common factor-based defactored instrumental variable technique useful for both homogeneous and heterogeneous slope dynamics that control for panel estimation challenges including endogeneity, omitted-variable bias, fixed-effects, and cross-section dependence.

The subsequent sections outline the extant literature focusing on three interconnected themes namely research and development and its linkage with green energy innovation, industrial structure dynamics, and energy intensity vs. green energy innovation. Section three highlights the empirical methodology, section four reports the empirical results whereas section five presents the discussion and conclusion of the study.

2. Review of Literature

A summary of existing literature on green energy innovation, research and development, and energy intensity is depicted in Chart 1.

2.1. Energy Research & Development vs. Green Energy Innovation

Heightened research and development (R&D) are highly regarded among several countries, especially the more developed countries (MDCs)—due to the realization that R&D is the wheel of technological advancement. Energy R&D has received much attention and adoption, due to the harmful effects of conventional energy sources namely coal, oil, and gas. Concerns of global warming, climate change, rapid deforestation, and resource depletion have spurred research into sourcing for clean and sustainable options. The influence of energy R&D is given much priority in the extant literature. For example, a study adopted linear regression analysis and dynamic panel threshold model to assess the effects of technological progress and structural change on energy intensity [7]. Domestic R&D is found to have the highest effect on energy intensity reduction, along with both internal and external technological acquisition. The findings showed 1% rise in home-grown R&D capital stock leads to 0.31% decline in energy intensity. Other studies are not far off with their submission that technological innovation through research and development is a vital tool in propagating sustainable energy in industries [12]. However, the high costs of R&D coupled with low levels of investment are two key factors behind stunted technological innovation in least developed countries (LDCs). In contrast, rising energy prices have a knockback effect on R&D investment by reducing profits. However, the rising costs could spur more firms into energy-saving efforts, which would later increase firm innovation [8]. Despite the considerable efforts made by other countries in research into driving green innovation, it pales in contrast to OECD countries at the zenith of industrialization—with implementation of other technical indicators requiring further development and progress [11]. From another perspective, the influence of government control in addition to economic interference in making strides to drive research and development include tax holidays, tax reliefs, incentives, and subsidies. Although, they could have uncertain effects as the funds allocated or saved could either be used in green R&D or non-green R&D. For instance, firms with more environmental subsidies were found to engage in more non-green innovation than green innovation [13].

Objectives	Author & Year	Study Period	Methodology	Findings
Explore the relationship between China's environmental innovation and macroeconomic green productivity	Yan, Zou, Du, Li (2020)	2000-2015	Luenberger productivity indicator	Global green innovations to curb climate change
Examine the impact of green technology innovations on carbon dioxide emissions	Du, Li, Yan (2019)	1996-2012	Panel threshold model	Green technology innovations decline emissions
Examine the drivers of Green Innovation that led a set of local suppliers to successfully undertake GI in the Peruvian mining industry	Aron, Molina (2019)	2010–2017	Participant Interview	Green innovations in firms require highly specialized workforce
Assess the nexus between Green supply chain collaborative innovation absorptive capacity and innovation performance	Hong, Zheng, Deng, and Zhou (2019)	N/A	Close-ended questionnaire	Internal mechanism promotes innovation performance
Examine the nexus between the various components of an enterprise's green technological innovation ability and enterprise competitiveness	Li, Wang, Su, Su (2019)	2011-2016	Panel data	Green innovation research and development enrich enterprise knowledge
Assess the effect of technological innovation on green growth	Mensah, Long, Dauda, Boamah, Salman, et al. (2019)	2000-2014	STIRPAT, IPAT and multiple linear regression	Energy consumption is detrimental to green growth
Examine the marginal effect and threshold effect of regional innovation on energy consumption	Hao, Deng (2019)	2005-2015	Panel varying coefficient and threshold model	Regional innovation and energy use upgrade is non-linear
Assess the heterogeneous effects of green technology innovations on carbon productivity	Du, Li (2019)	1992–2012	Parametric Malmquist index approach	Technological progress improves carbon productivity
Examine whether energy technology innovations are beneficial for carbon dioxide emissions abatement in China	Wang, Zhu (2020)	2000-2017	Panel data	carbon dioxide emissions abatement depends on energy innovations
Assess the impact of policy on renewable energy innovations	Samant, Thakur-Wernz, Hatfield (2020)	2000–2015	Comparative case studies	Pull policy countries focus on mature technologies
Explore the total factor energy efficiency and evaluate technological innovation	Wang, Wang (2020)	2001 -2013	Data Envelopment Analysis and Malmquist-Luenberger index	Technological innovation promotes total factor energy efficiency
Assess the effects of energy innovations on environmental quality	Solarin, Bello (2020)	1974-2016	STIRPAT	Energy innovations significantly improves environmental quality
Explore the relationship between public-private partnership investments in energy sector and carbon dioxide emissions	Shahbaz, Raghutla, Song, Zameer, Jiao (2020)	1984-2018	Bootstrapping Autoregressive Distributed Lag	Investments in energy impedes quality of the environment
Study the effect of technological progress and structural change on energy intensity	Luan, Huang, Zou, Huang (2020)	2000-2010	Dynamic panel threshold model	Indigenous R&D boosts the technical effects of energy intensity
Assess the impact of green innovation on energy intensity	Wurlod, Noailly (2018)	1975-2005	Translog cost function	Green innovations decline energy intensity
Assess the effect of environmental regulation on green productivity	Peng (2020)	2005-2015	Global Moran I index	Environmental regulation affects green productivity growth
Study the effect of energy price on firms' innovation	Kong, Yang, Xu (2020)	2003-2016	Quantile Regression	Rising energy prices affect manufacturing firms' innovation output
Assess the effect of environmental regulations and on urban green innovation	Zhang, Kang, Li, Ballesteros-Perez, et al. (2020)	2003-2016	Slacks-based measure of directional distance functions	Market regulations are more efficient in stimulating green innovation
Explore how green restructuring unfolds globally	Trippl, Baumgartinger-Seiringer, et al. (2020)	N/A	Descriptive statistics	Green shifts unfold via diversification, path creation and importation

Chart 1. Existing Literature on Green Energy Innovation, Research and Development, and Energy Intensity.

2.2. Industrial Structure vs. Green Energy Innovation

The strength, manner, and pattern of industries can either spur or impede green energy innovation in myriad ways. Both MDCs and LDCs seek to adopt more environmentally-friendly means of energy in the face of climate change and environmental degradation.

Nevertheless, the transitional process differs from region to region. Gathering data from 282 respondents in a manufacturing sector in Pakistan, Shahbaz, Raghutla [1] concluded that industrial growth has improved demand for natural resources, hastening environmental degradation. In another study on heterogeneous effects of green technology innovations on carbon productivity across 71 economies with different income levels, empirical evidence supporting the validity of the environmental Kuznets curve (EKC) was found [14]. Thus, many large LDCs are at the peak on the EKC, thereby slowing down green energy innovation due to heavy reliance on fossil fuels. Another industrial-based study that explores how green restructuring unfolds in regions across countries found a structural deficit that requires attention [5]. The study noted that a binding similarity among LDCs is weak industrial structure coupled with deficiency in expertise and assets, which are inimical to green path development. The concept of linkages and supply chains has not been left out in the literature. The interdependence of industries and smooth supply chain are crucial for the efficient operation of economies, especially in output creation. A case study of an automobile firm in China concluded that green innovation is more effective when support from supply chains is present and more evident in industries with lots of linkages [10]. This resonates with current research that examined the factors behind green innovation in the Peruvian mining industry [15]. Findings show that suppliers in the mining value chain have a high level of human capital and significant technology driving innovations. Green innovation is reported to develop in industries where firms are more embedded and engaged in more knowledge-sharing activities [16].

2.3. Energy Intensity vs. Green Energy Innovation

The concept of energy intensity has certainly intensified in recent years, with a rising number of studies on the theme. Reducing the amount of energy consumed in manufacturing is a mainstay of developmental plan of governments across the globe—leading to increased attention on green innovations [6]. The vast majority of literature attempts to ascertain factors behind the rise and fall, determinants, and relationship with other sources and dynamics of energy. A common observation exists among countries like the US, China, and Korea. These countries are among the highest energy consumers and unsurprisingly, are among the highest global polluter of CO₂ emissions. The US is second only to China in terms of carbon emission, and these countries are among the leaders in green innovation, with inventions like artificial photosynthesis, 3D-printed wind-solar energy tubes, and carbon nanotube electricity [17]. Green technology innovations can enhance energy efficiency by improving total factor carbon productivity through its mitigation effects [14]. However, a study on the impact of green innovation on energy intensity in OECD nations found that the falling energy intensity across OECD countries was associated with industrial energy efficiency rather than the utilization of environmentally-friendly energy sources [3]. A study found a feedback relationship between energy intensity and green energy innovation, implying a positive monotonic effect of increasing energy intensity to technological innovations [9]. Conversely, soaring levels of green innovation decrease energy intensity. In curbing intensity, measures put in place to reduce energy intensity have both short and long-run effects, thereby breeding uncertainty. The negative short-run effect refers to the cost increment due to compliance with government regulatory efforts alongside the disruption of current operational activities. However, the long-run effect, which is more significant, involves switching to technological innovation—which allows firms to offset earlier costs incurred [6]. In contrast, trade openness, government environmental spending, and income-induced technique effect are reported to improve energy efficiency in Korea [18]. Surprisingly, the green growth strategy implemented in 2009 has had less impact in reducing energy intensity than the aforementioned factors. Beyond energy intensity, other authors outline the impact of environmental regulation on green innovation. Though originally implemented to combat climate change and other ill-effects of carbon emissions, environmental regulation has been discovered to propel green innovation. Environmental regulation is regarded to project a middle course between economic

progress and environmental pollution whereas technological innovation is regarded to reduce green total factor efficiency [6,19].

3. Methods

Data utilized in this study are employed from IEA and OECD [20]. The selection of countries and data period is due to data availability—to prevent estimation challenges attributed to the unevenly spaced dataset. Our conceptual framework is centered on achieving sustainable development goals namely reducing production, consumption, emissions, and improving modern energy technologies.

To examine the nexus between anthropogenic emissions, green energy-based innovations, and energy intensity, we employed novel econometric techniques including Granger Causality (time series model) and common factor-based defactored instrumental variable (panel model). Causality relies on economic theory to provide reasons for causal nexus between economic variables [21]. The Granger Causality is a widely used and popular econometric tool majorly used to empirically verify causal relationships among sampled variables. The technique was adopted to ascertain the causal link between money and income in the US [22]. Hence, the flexibility of Granger Causality springs from its suitability to stochastic nature of myriad variables and not a structural model [21].

The forward recursive, rolling window and recursive rolling algorithm are three change point methods that are data-driven. These approaches can be used to establish causal relationships without initially detrending the data. However, amongst the three techniques, the rolling window presents reliable results inferred from simulation experiments. The recursive rolling algorithm follows the forward recursive algorithm rounding off the list. In detecting changes in causality, the rolling window algorithm is preferred [22]. However, all techniques work better when the change of causality occurs early in the sample. Certain factors affect the effectiveness of detection rates of the algorithms in opposite ways. Window size has an inverse relationship with accurate detection rates—with direct relationship existing with the trio of sample size, strength, and duration of the causal relationship.

The recursive rolling algorithm was modified due to the sensitivity of Granger Causality to the time period of estimation, and thus, was improved to a recursive evolving algorithm [21]. Further simulations show the improved algorithm has superior change detection of socioeconomic, environmental, and energy indicators over the previous three techniques. The new algorithm involves calculating important statistics using the recursive techniques and providing an expansion of the sequence of samples—whereby the final observation for this observation becomes the current observation of interest. Empirically, this has been adopted in a few studies on the consumption and economic output relationship. To investigate the time-varying causality between green energy innovation and energy intensity, we used a novel causality procedure developed by Shi, Phillips [21], Shi, Hum [22] based on the recursive-evolving window. To expose this approach, y_t is defined as a k -vector time series generated by the following process:

$$y_t = \alpha_0 + \alpha_1 t + u_t \quad (1)$$

where u_t follow a $VAR(p)$ model

$$u_t = \beta_1 u_{t-1} + \dots + \beta_p u_{t-p} + \varepsilon_t \quad (2)$$

where ε_t is the error term. Substituting $u_t = y_t - (\alpha_0 + \alpha_1 t)$ from Equation (2) into Equation (1), we obtain

$$y_t = \gamma_0 + \alpha \gamma_1 t + \beta_1 y_{t-1} + \dots + \beta_p y_{t-p} + \varepsilon_t \quad (3)$$

where γ_i is a function of α_i and β_j with $i = 0, 1$ and $j = 1, \dots, p$.

Following Toda and Yamamoto [23], Dolado and Lütkepohl [24], the lag augmented VAR is used to implement Granger causality test for possible integrated variable y_t as:

$$Y = \tau\Gamma' + X\Theta' + B\Phi' + \varepsilon \quad (4)$$

where $Y = (y_1, \dots, y_T)'_{T \times n}$, $\tau = (\tau_1, \dots, \tau_T)'_{T \times 2}$, $\tau_t = (1, t)'_{2 \times 1}$, $X = (x_1, \dots, x_T)'_{T \times np}$, $x_t = (y'_{t-1}, \dots, y'_{t-p})'_{np \times 1}$, $\Theta = (\beta_1, \dots, \beta_p)_{n \times np}$, $B = (b_1, \dots, b_T)'_{T \times nd}$, $b_t = (y'_{t-p-1}, \dots, y'_{t-p-d})'_{nd \times 1}$, $\Phi = (\beta_{p+1}, \dots, \beta_{p+d})_{n \times nd}$ and $\varepsilon = (\varepsilon_1, \dots, \varepsilon_T)'_{T \times n}$. d is the maximum order of integration for y_t .

Based on the null hypothesis $H_0 : R\theta = 0$, the Wald test is defined by

$$w = [R\hat{\theta}]' [R(\hat{\Omega} \otimes (X'QX)^{-1})R']^{-1} [R\hat{\theta}] \quad (5)$$

where $\hat{\theta} = \text{vec}(\hat{\Theta})$ represents the row vectorization with $\hat{\Theta} = X'QX(X'QX)^{-1}$, $\hat{\Omega} = T^{-1}\hat{\varepsilon}'\hat{\varepsilon}$ and $R(m \times n^2p)$ is a matrix with m , the number of restrictions. Under H_0 and the assumption of conditional homoscedasticity, the Wald statistic is asymptotically χ_m^2 .

Following Shi, Phillips [21], the real-time-varying causality test used the supremum (sup) Wald statistic sequences based on recursive evolving algorithm [25,26]. The Wald statistic over $[f_1, f_2]$ with sample size fraction of $f_w = f_2 - f_1 \geq f_0$ is given by $W_{f_2}(f_1)$ and sup Wald statistic is denoted by:

$$SW_f(f_0) = \sup_{(f_1, f_2) \in \wedge_0, f_2 = f} \{W_{f_2}(f_1)\} \quad (6)$$

where $\wedge_0 = \{(f_1, f_2) : 0 < f_0 + f_1 \leq f_2 \leq 1, \text{ and } 0 \leq f_1 \leq 1 - f_0\}$ for some minimal sample size $f_0 \in (0, 1)$ in the regressions.

In the case of the recursive evolving algorithm, the dating rules for a simple switch case are given by:

$$\hat{f}_e = \inf_{f \in [f_0, 1]} \{f : SW_f(f_0) > scv\} \text{ and } \hat{f}_f = \inf_{f \in [\hat{f}_e, 1]} \{f : SW_f(f_0) < scv\} \quad (7)$$

where cv and scv represent respectively the critical values of W_f and SW_f statistics. \hat{f}_e and \hat{f}_f denote the estimated first chronological observations when the test statistics exceeds or falls below the critical values for the origination and termination points in the causal relationship, respectively. Besides, the origination and termination dates are computed analogously for multiple switches.

Next, we construct panel-based models to examine the long-term association between energy research and development, energy intensity, and industrial structure in both emissions and green energy innovation function. In panel data settings, several estimation challenges persist, affecting the validity of the parameters. Such challenges include unobserved heterogeneous effects, cross-section dependence, and omitted-variable and misspecification bias [27]. Thus, controlling these challenges requires modern and sophisticated common factor estimation methods. This study adopts the novel common factor-based defactored instrumental variable technique useful for both homogeneous and heterogeneous slope dynamics while accounting for endogeneity, omitted-variable bias, fixed-effects, and cross-section dependence [28]. The flexibility of the proposed model in terms of computation, technicalities, and parameter specification outweighs existing traditional panel estimation procedures. For example, existing panel methods require the extension of parameters with outgrowth in either the data period (T) or cross-sectional dimension (N)—leading to potential incidental parameter bias [29]. The proposed model

following the novel common factor-based defactored instrumental variable technique can be expressed as:

$$\begin{aligned}
 Y_{i,t} &= \alpha Y_{i,t-1} + \beta_1 A_{i,t} + \beta_2 B_{i,t} + \beta_3 [C_{i,t} - C_{i,t-1}] + \beta_4 D_{i,t} + v_{i,t}; v_{i,t} \\
 &= \eta_{i,t} + \tau_t + \gamma'_{y,i} f_{y,t} + \varepsilon_{i,t}
 \end{aligned}
 \tag{8}$$

where $Y_{i,t}$ represents the dependent variables namely fossil emissions and green energy innovations. $\alpha < 1$ denotes the autoregressive parameter that inhibits countries from achieving optimal levels. $Y_{i,t-1}$ is the lagged-dependent series; β_1, \dots, β_4 are the estimated slope coefficients. A, \dots, D denote the covariates, however, $C_{i,t} - C_{i,t-1}$ is the historical fossil emissions. $v_{i,t}$ represents the idiosyncratic error term, $\eta_{i,t}$ and τ_t capture the country-specific and time-specific effects, $\gamma'_{y,i} f_{y,t}$ and $\varepsilon_{i,t}$ are the unobserved factors, factor loadings, and idiosyncratic error, respectively.

4. Results

The time-varying causality procedure does not need prefiltering of the data but requires the maximum order of integration for the VAR [22]. Based on the Augmented Dickey-Fuller (ADF) unit root test (Table 1), we find that the maximum order of integration is one [I(1)] for all countries except for the United States with I(2) characteristic. We implement the time-varying Granger causality analysis based on a lag augmented VAR model with $d = 1$ for all countries and $d = 2$ for the United States.

Table 1. ADF unit root test results.

Country	GEI			ENI		ERD		INS		Max Order of Integration (d)
	Level	1st Diff	2nd Diff	Level	1st Diff	Level	1st Diff	Level	1st Diff	
Australia	0.5389	0.0001 ^a	-	0.0205 ^b	-	0.1752	0.0940 ^c	0.9375	0.0001 ^a	1
Austria	0.4168	0.0000 ^a	-	0.0570 ^c	-	0.9117	0.0000 ^a	0.4181	0.0018 ^a	1
Belgium	0.2268	0.0000 ^a	-	0.4808	0.0002 ^a	0.8835	0.0009 ^a	0.0418 ^b	-	1
Canada	0.5808	0.0000 ^a	-	0.5482	0.0003 ^a	0.0805 ^c	-	0.3881	0.0001 ^a	1
Denmark	0.0206 ^b	-	-	0.2199	0.0000 ^a	0.1341	0.0011 ^a	0.1419	0.0000	1
Finland	0.0005 ^a	-	-	0.0558 ^a	-	0.4434 ^a	0.0000 ^a	0.4388	0.0014 ^a	1
France	0.8941	0.0000 ^a	-	0.1336	0.0001 ^a	0.5734	0.0000 ^a	0.9660	0.0000 ^a	1
Germany	0.2848	0.0000 ^a	-	0.8084	0.0003 ^a	0.9937	0.0000 ^a	0.9909	0.0000 ^a	1
Greece	0.0032 ^a	-	-	0.8923	0.0000 ^a	0.2407	0.0010 ^a	0.6742	0.0002 ^a	1
Ireland	0.0127 ^b	-	-	0.1308	0.0000 ^a	0.7849	0.0001 ^a	0.2217	0.0001 ^a	1
Italy	0.7240	0.0022 ^a	-	0.5021	0.0000 ^a	0.8593	0.0002 ^a	0.9567	0.0000 ^a	1
Japan	0.5737	0.0001 ^a	-	0.3695	0.0002 ^a	0.2000	0.0021 ^a	0.2320	0.0000 ^a	1
Netherlands	0.6747	0.0001 ^a	-	0.1782	0.0000 ^a	0.0006 ^a	-	0.6840	0.0000	1
New Zealand	0.0495 ^b	-	-	0.0652 ^c	-	0.5587	0.0206 ^b	0.7244	0.0000 ^a	1
Norway	0.0008 ^a	-	-	0.0319 ^b	-	0.2930	0.0004 ^a	0.3717	0.0000 ^a	1
Portugal	0.6715	0.0000 ^a	-	0.9628	0.0000 ^a	0.8283	0.0000 ^a	0.4278	0.0000 ^a	1
Spain	0.3100	0.0000 ^a	-	0.9485	0.0000 ^a	0.2599	0.0001 ^a	0.1234	0.0859 ^c	1
Sweden	0.0169 ^b	-	-	0.1529	0.0050 ^a	0.8207	0.0000 ^a	0.0978 ^c	-	1
Switzerland	0.6379	0.0001 ^a	-	0.4429	0.0001 ^a	0.0002 ^a	-	0.9455	0.0006 ^a	1
United Kingdom	0.5625	0.0004 ^a	-	0.2865	0.0000 ^a	0.9892	0.0010 ^a	0.8518	0.0003 ^a	1
United States	0.4685	0.3029	0.0000 ^a	0.9235	0.0002 ^a	0.8873	0.0000 ^a	0.9533	0.0002 ^a	2

Notes: Figures denote *p*-values. ^{a,b} and ^c indicate the rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively. GEI: Green Energy Innovation; ENI: Energy Intensity; ERD: Energy Research and Development; and INS: Industrial Structure.

The results of time-varying causality between green energy innovation, energy intensity, energy research development and demonstration, and industrial structure are presented in Table 2. A significant causality is detected if the Wald statistic sequence exceeds its corresponding critical value during a period. We observe a significant bidirectional

time-varying causality running from green energy innovation to industrial structure for all countries under investigation—except for Austria with no causal effect detected. Contrary to Chakraborty and Mazzanti [20], our results suggest the effect of green innovations on energy intensity is uniform across OCED countries. From a policy perspective, OCED countries have instituted—important energy strategies, investment in R&D, and promote green technologies to reduce energy intensity and abate anthropogenic emissions.

Table 2. Time-varying Granger causality results.

Country	ENI to GEI	GEI to ENI	ERD to GEI	GEI to ERD	INS to GEI	GEI to INS
Australia	1993–2014	1995–2014	1995–2014	1995–2014	1996–2014	1995–2014
Austria	2009–2014	2002–2004 2006–2008 2011–2012	1990/1997/ 1999 2002–2005 2010 2013–2014	1996–2014	2002–2003 2005 2007–2014	-
Belgium	1989 1991–2014	1991 1995–2014	1995–2014	1993 1995–2014	1990 1995–2014 1996–1998	1995–2014
Canada	2006 2008–2014	1992–2014	2000/2003/ 2005/2010/ 2014	1992–2014	2000 2002–2014	1992–2014
Denmark	1990–1991 1993–2014	1992 1995–2014	1995–2014	1995–2014	1989 1994 1996–2014	1995–2014
Finland	1995–1996 1998–2014	1988–1995 1997–2014	1990 1998 2000–2014	1988–2014	1991 1996 1998 2000–2014	1988–2014
France	1990–1991 1993 1995–2014	1994–2014	1990 1995–2014	1995–2014	1995–2014	1995–2014
Germany	1990–2014	1990–2014	1990–2014 1996	1990–2014	1990–2014	1989–2014 1998
Greece	2008–2009 2011–2014	1997–2014	2008 2010–2012 2014	2007 2013–2014	1999–2001 2003–2014	2002 2009 2014
Ireland	2014	1997 2013	1991–1992 1997–2001 2003–2004 2006 2008–2014	2006–2007 2009–2010 2013–2014	2000–2014	2006 2010
Italy	1997–2014	1992–1994 1997–2014	1999 2001–2014	1994 1997 2000–2014	1993 1996–2014	1993–1999 2001–2014
Japan	2008–2014	1993–1994 1996–2014	2010–2011 2013–2014	2014	1996–2014	1994–2014
Netherlands	1992 1994–2014	1996–2014	1995–2014	1991 1996–2014	1990 1992–1993 1996–2014	1992 1996–2014
New Zealand	2008–2014	1987–2014	1992 2009 2013–2014	1987–1988 1990–1992 1994–1996 1998–2014	2004–2006 2008 2010 2012–2014	1987–2014

Table 2. Cont.

Country	ENI to GEI	GEI to ENI	ERD to GEI	GEI to ERD	INS to GEI	GEI to INS
Norway	1997–1998 2000–14	1992–1994 1997–1998 2000–2014	1999–2014	1992 1994 1997–2014	1991 1995 1997–1998 2000–2014	1992 1994 2000–2014
Portugal	2013–2014	1992–2014	2002 2009–2010 2012 2014	1992–2014	2001–2003 2005–2007 2009–2014	1992–2014
Spain	1992–2014	1993 1995–2014	1988 1995–2014	1993 1995–2014	1988 1990–2014	1995–2014
Sweden	1997–2014	1991–1994 1996–2014	2001–2014	1989 1994 1997–2014	1989 1992 1994 2000–2014	1996–1997 1999–2014
Switzerland	1995–2014	1999–2014	2000–2014	1999–2014	1990 1993 1999–2014	2001–2014
United Kingdom	1995–1996 1998–2014	1999–2014	1985 1996 1999–2014	1991 2000–2014	1997 2001–2014	1995–1997 1999–2014
United States	1999–2014	1990–2014	2005–2014	1990–2014	1998–2001 2005–2014	1990–2014

Notes: The periodic statistics (e.g., 1990–2014) denote the period of causalities if time-varying causality exists. GEI: Green Energy Innovation; ENI: Energy Intensity; ERD: Energy Research and Development; and INS: Industrial Structure.

The estimated heterogeneous properties presented in Figures 1–3 show the mean, variance, and autocorrelation distributional features within the 95% confidence band. This outcome underscores potential heterogeneity in green energy innovation, industrial structure, energy intensity, energy research & development, and fossil emissions across countries. The distributional heterogeneous mean in Figure 1 reveals a significant degree of long-term disparities in all sampled indicators across carbonized high-income countries. However, the distributional heterogeneous variance in Figure 2 between countries is relatively close in the spread—indicating the potentiality of a common factor. The autocorrelation heterogeneous distribution in Figure 3 shows evidence of sample deviations that exhibit a positive serial correlation. The heterogeneous effects evidenced can be attributed to unobserved factors and persistent socio-economic, environmental, and energy dynamics.

We developed a baseline dynamic fixed-effects model in both green energy innovation and fossil emission functions presented in Figures 4 and 5. In both model functions, we incorporate lagged-dependent variables to account for omitted-variable and misspecification bias. Second, we account for inertia effects due to historical tendencies that depict future occurrences. Importantly, we account for historical fossil emissions by using the expression: $Hist = (Fossil_t - Fossil_{t-1})$. The estimated parameter in Figure 4A shows significant positive lagged-dependent green energy innovation (0.52)—validating potential inertia effects. Likewise, a significant positive coefficient (0.01) is observed in Figure 4D, implying growth in energy R&D improves green energy innovation. In contrast, insignificant negative coefficient (−0.10) is observed in Figure 4B, showing that historical fossil emissions are not meaningful in negating growth in green energy innovations. However, Figure 4C shows a significant negative coefficient (−0.83)—inferring that outgrowth in energy intensity declines long-term inclusion of green innovation in the energy portfolio. Besides, a significant negative coefficient (−0.28) is observed in Figure 4E, implying growth in industry structure worsens the adoption of green energy innovations.

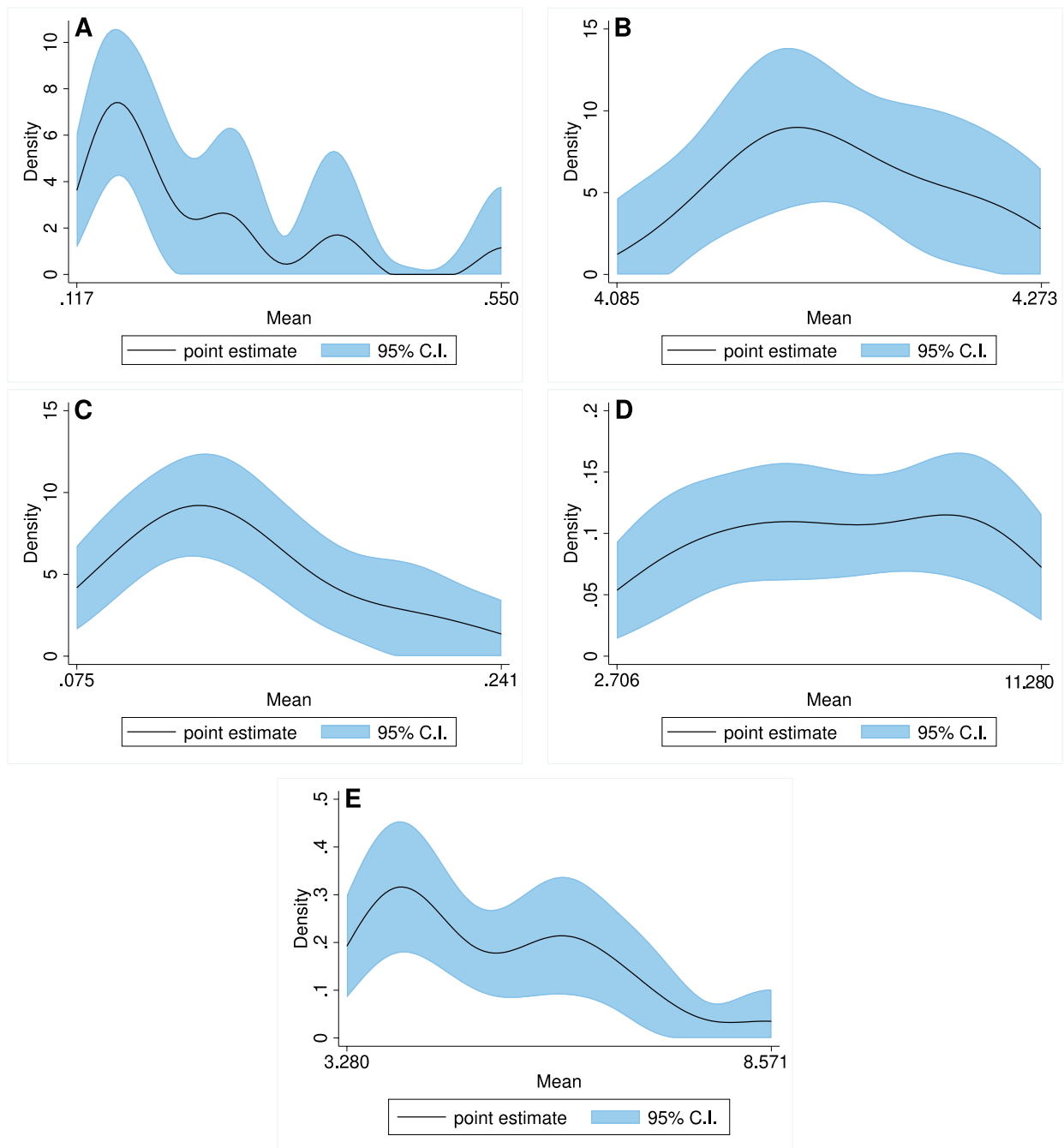


Figure 1. Mean heterogeneous distribution across countries: (A) Green Energy Innovation (B) Industrial Structure (C) Energy Intensity (D) Energy R&D (E) Fossil emissions.

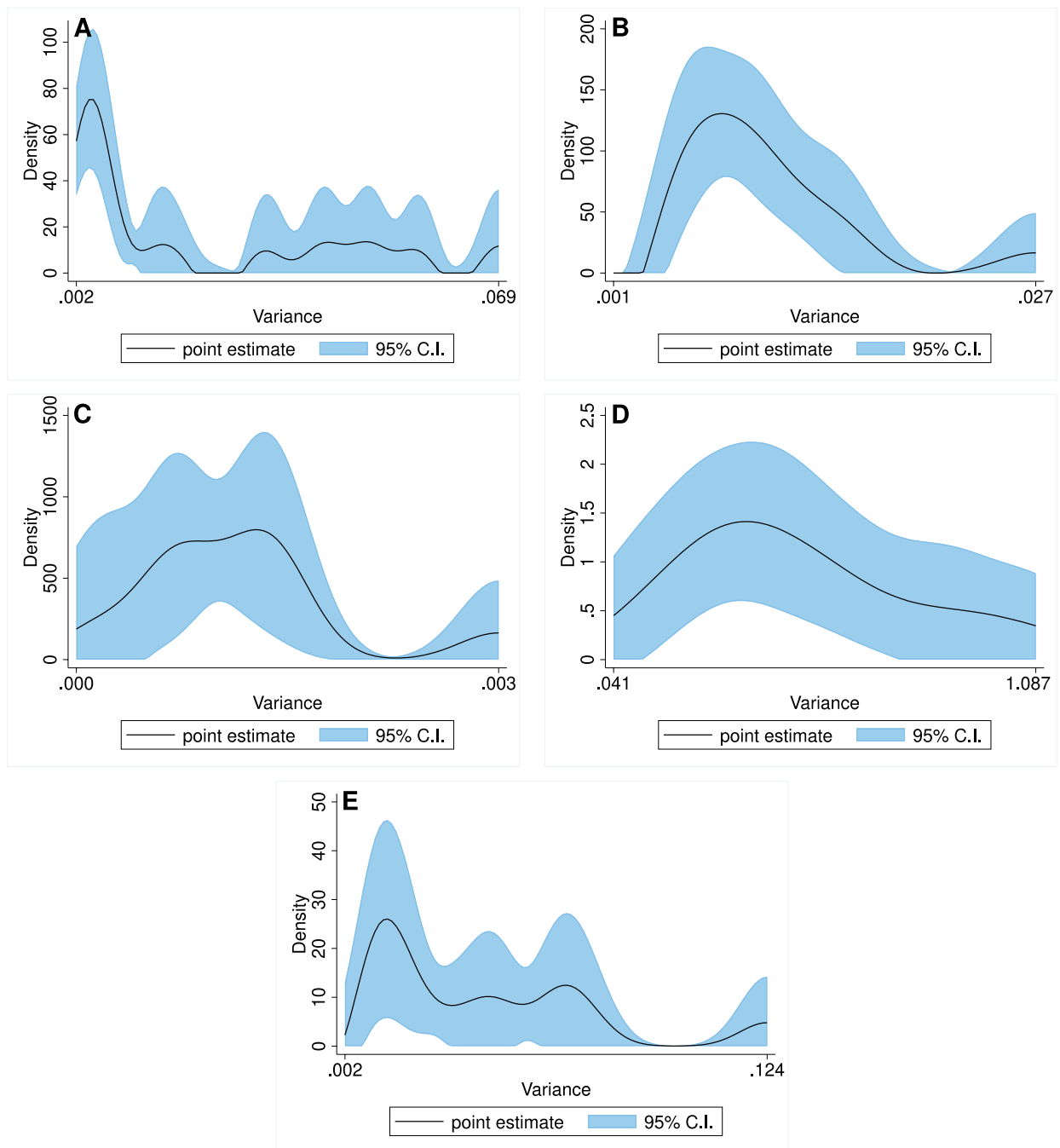


Figure 2. Variance heterogeneous distribution across countries: (A) Green Energy Innovation (B) Industrial Structure (C) Energy Intensity (D) Energy R&D (E) Fossil emissions.

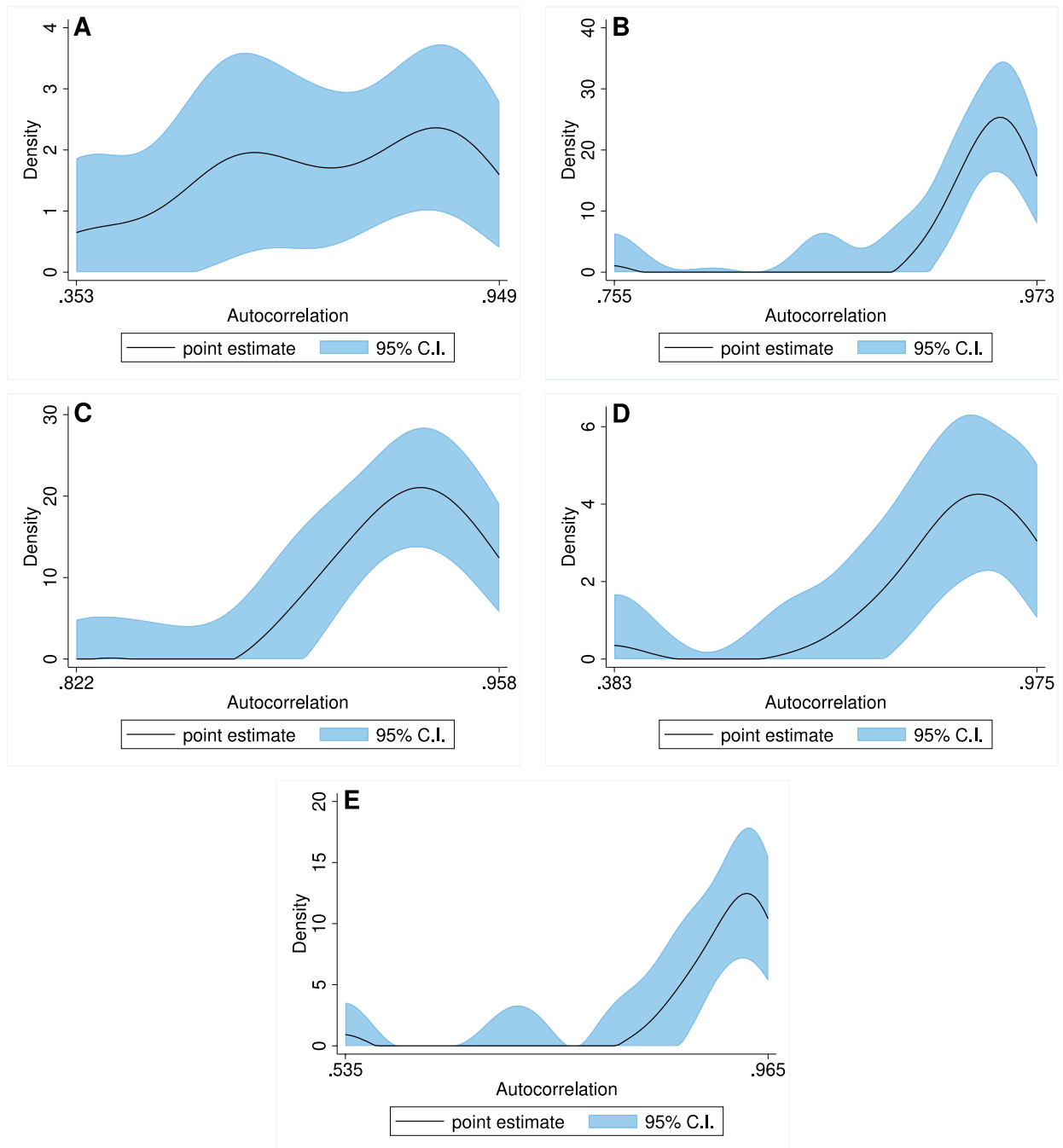


Figure 3. Autocorrelation heterogeneous distribution across countries: (A) Green Energy Innovation (B) Industrial Structure (C) Energy Intensity (D) Energy R&D (E) Fossil emissions.

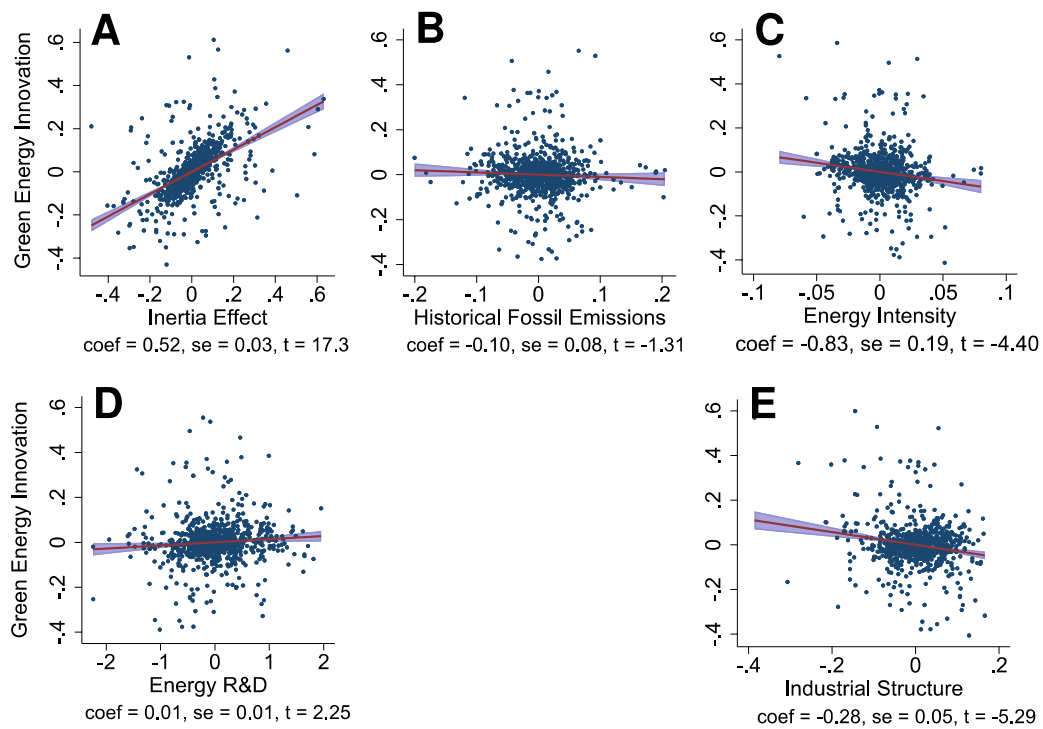


Figure 4. Baseline fixed-effects model in green energy innovation function: (A) Inertia Effect (B) Historical Fossil Emissions (C) Energy Intensity (D) Energy R&D (E) Industrial Structure.

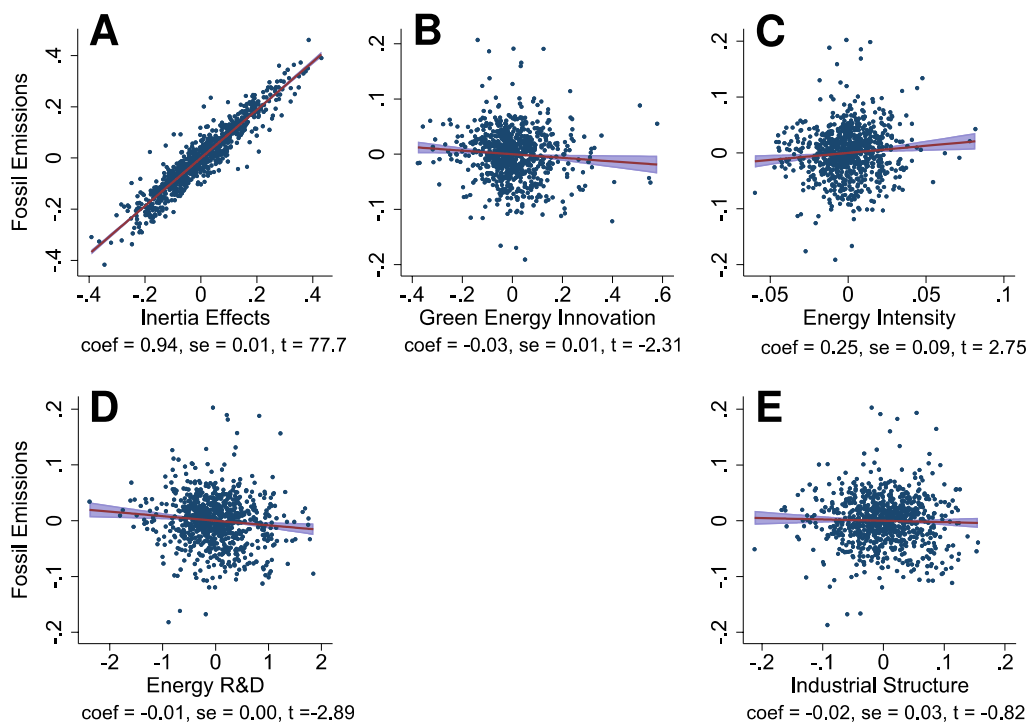


Figure 5. Baseline fixed-effects model in fossil emissions function: (A) Inertia Effect (B) Green Energy Innovation (C) Energy Intensity (D) Energy R&D (E) Industrial Structure.

In the fossil emissions function in Figure 5, the estimated coefficient in Figure 5A reveals significant positive lagged-dependent fossil emissions (0.94)—validating potential inertia effects of historical fossil emissions. Likewise, the parameter (0.25) on energy intensity in Figure 5C is significantly positive, revealing that expansion in energy intensity

escalates fossil emissions. In contrast, a significant negative coefficient (-0.03) is evident in Figure 5B—deducing that expanding the inclusion of green energy innovation in the energy portfolio has long-term fossil emission mitigation effects. Likewise, the parameter on energy R&D depicted in Figure 5D is statistically negative (-0.01), showing that growth in energy R&D declines fossil emissions. However, the insignificant negative coefficient (-0.02) observed in Figure 5E shows that growth in industrial structure is not meaningful in negating growth in fossil emissions.

Next, we developed instrumental variable-based (IV) models that account for unobserved common factors and heterogeneous slope dynamics—challenges in existing panel-based estimation techniques (Table 3). The first three instrumental variable-based models namely single-equation estimated two-stage least squares estimator (IV—2SLS [column 2]), first-step estimator (IV—1st-step estimator [column 3]), and second-step estimator (IV—2nd-step estimator [column 4]). All the three models are estimated based on homogeneous slope parameters, however, IV—2SLS model accounts for year and country fixed-effects with single-equation instrumental variable whereas IV—1st-step and V—2nd-step estimators incorporate defactored instrumental variables by absorbing both year and country fixed-effects. In contrast, model four in fossil emission function accounts for heterogeneous slope dynamics with defactored instrumental variables that absorb both year and country fixed-effects (IV—MG estimator [column 5]). The IV—MG technique employs instrumental variable-based mean-group estimator useful for producing consistent and robust dynamic parameters [28]. Model 5 employs dynamic Drisc-Kraay fixed-effects estimator (D/K—FE estimator [column 7]) in green energy innovation function. The D/K—FE estimator produces robust standard errors by controlling for potential heteroskedastic error structure and cross-sectional dependence across countries [30]. The resultant estimated parameters presented in Table 3 (columns 2–5) reveal positive lagged-fossil emissions in two homogeneous slope models and the IV—MG model, confirming the results of the baseline model in fossil emission function. However, estimations based on IV—2SLS and IV—MG are statistically significant at p -value < 0.01 . Similar to the baseline model, a positive green energy innovation coefficient is reported in all models, supporting the argument that evolution in green energy innovation declines long-term fossil emissions. The parameter on energy intensity in both homogeneous and heterogeneous models is significantly positive—corroborating the baseline model. This infers that growth in energy intensity intensifies fossil emissions. Contrary to the baseline model, the coefficient on energy R&D is positive and statistically significant at p -value < 0.01 in all models excluding IV—MG. The potential difference may be attributed to the inclusion of defactored instrumental variables that may perhaps control for potential unobserved common factors. The heterogeneous slope model shows a significant negative coefficient of industrial structure compared to the insignificant negative coefficient in the baseline model. This reveals that controlling heterogeneous effects of industrial structure growth is meaningful in mitigating fossil emissions. The green energy innovation function in Table 3 column 7 produces similar but robust and significant parameters compared to the baseline model. The estimated coefficient (Green Energy $_{t-1}$) is significantly positive at p -value < 0.01 —revealing that historical green innovations influence future adoption of green energy innovations in the energy mix. Corroborating the baseline model, 1% growth in energy R&D improves green energy innovation by 0.01%. In contrast, 1% proliferation of historical fossil emissions thwarts the development of green energy innovations by 0.1%. Besides, the effect of energy intensity due to industrial structure expansion declines the continual inclusion of green innovation in the energy portfolio.

Table 3. Instrumental Variable-based Panel Emissions and Green Energy Parameter Estimates.

Emission Parameters	IV—2SLS	IV—1st-Step Estimator	IV—2nd-Step Estimator	IV—MG	Green Energy Parameters	D/K—FE
Emissions _{t-1}	0.554 *** (0.093)	−0.002 (0.129)	0.015 (0.069)	0.646 *** (0.072)	Green Energy _{t-1}	0.517 *** (0.084)
Green Energy	−0.126 *** (0.046)	−0.025 (0.051)	−0.032 *** (0.011)	−0.041 (0.035)	Historical Emissions	−0.100 * (0.055)
Energy Intensity	1.654 *** (0.618)	2.731 *** (0.804)	1.897 *** (0.602)	2.573 *** (0.636)	Energy Intensity	−0.834 *** (0.134)
Energy R&D	0.024 *** (0.009)	0.024 ** (0.010)	0.022 *** (0.005)	0.008 (0.006)	Energy R&D	0.014 ** (0.006)
Industrial Structure	0.236 (0.177)	0.157 (0.282)	0.100 (0.172)	−0.298 *** (0.140)	Industrial Structure	−0.284 ** (0.121)
Constant	—	3.922 *** (1.302)	4.200 *** (1.092)	2.519 *** (0.676)	Constant	1.304 ** (0.533)
Observations	798	798	798	798	Observations	819
Wald chi ² (62)	688.040	15.5725	13.2672	—	Prob > F	0.000 ***
Prob > chi ²	0.000 ***	0.0293	0.0659	—	within R-squared	0.395
R-squared	0.998	—	—	—	R-squared	—
Root MSE	0.056	—	—	—	Root MSE	—
Year Fixed-effects	Yes	Yes	Yes	Yes	Year Fixed-effects	No
Country Fixed-effects	Yes	Yes	Yes	Yes	Country Fixed-effects	No
Δ	37.275 ***	37.275 ***	37.275 ***	37.275 ***	Δ	16.978 ***
Δ _(adj)	40.430 ***	40.430 ***	40.430 ***	40.430 ***	Δ _(adj)	18.458 ***
Hansen Test	—	15.573 ††	13.267 †	—	—	—

Notes: ***, **, * denote statistical significance at $p < 0.01$, $p < 0.05$, $p < 0.10$. IV—2SLS: single-equation instrumental variable (IV) regression, IV—1st-step estimator: defactored IV panel regression based on 1st-step estimator, IV—2nd-step estimator: defactored IV panel regression based on 2nd-step estimator, IV—MG: defactored IV panel regression based on mean group estimator, and D/K—FE: Drisc-Kraay fixed-effects estimator. †, †† represent the rejection of the validity of Hansen test for overidentifying restrictions at 5, 10% significance level.

5. Discussion and Conclusions

This study examined the impact of green energy innovation, energy research and development, energy intensity, and industrial structure on emissions across OECD countries. We further explored the role of historical emissions, energy intensity, among other covariates in inducing green energy-based innovations. The growing interest in energy research and development can be attributed to the harmful effects of climate change and its impacts due to the overdependence on fossil fuel technologies, rapid deforestation, urban sprawl, economic productivity, and natural resource depletion [31–33]. Our empirical assessment highlights the importance of energy research and development in expanding green energy innovations while reducing emissions. Similarly, investment in green energy innovation and research and development are reported to decline greenhouse gas emissions [34]. Green innovations improve energy efficiency by improving total factor carbon productivity [14]. However, continual reliance on obsolete energy research and development may worsen environmental sustainability. Reduction in fossil-related emissions by 231–289% in the US is accredited to research and development efficiency and intensity [35]. While there exists a tradeoff between economic productivity and environmental sustainability, the inclusion of green energy technologies—a magic bullet—appears a game-changer without compromising both desirables. Technological innovation through research and development is reported to proliferate the adoption of sustainable energy technologies in industries [12]. Notwithstanding, several studies raise concerns about the acquisition and deployment of such useful green energy technologies. Sustaining green energy technologies depends largely on country-specific policies and instruments, which in turn affects the availability, accessibility, and affordability (cost) of technological innovations [4]. This possibly explains the role of historical green energy innovations in dictating future inclusion of green energy innovations in the energy portfolio across high-income countries. However, market failure for research and development, and low

patronage of green energy technologies in developing countries can be attributed to the environmental and economic cost of modern innovations [4,36]. It is reported that high costs of energy research and development combined with low levels of private participation and public-private partnerships in energy investments are key causes of stunted technological innovation in developing economies [12]. Hence, subsidizing energy research and development is described to reduce carbon emissions by 8.52% from R&D without spillover, 5.98% from R&D with spillover from clean and renewable energy industry, and 9.55% from R&D investment [36]. Besides, the emission reduction effect of energy research and development is channeled through a reduction in energy intensity and technological acquisition [7]. However, our assessment shows that outgrowth in energy intensity escalates fossil emissions while reducing green energy innovations. Increasing demand for energy to sustain economic productivity is met through the reliance on fossil energy sources, hence, emphasizes the trend of fossil emissions due to energy intensity [37]. We find that the expansion of industrial structure declines both fossil emissions and green energy innovations. The composition of economic-based industries determines emission trends and share of green energy innovations. However, the pollution effect of industrial structure is determined by growth effect of energy-to-growth productivity, feedback effect of energy-to-growth productivity, and conservation effect of energy-to-growth productivity. Thus, countries that require high energy intensity levels for economic productivity have carbonized industrial structure whereas countries with low energy requirements to achieve economic productivity have low-carbon driven industrial structure. We demonstrate that green energy-based innovations and energy research and development play a critical role in achieving environmental sustainability—through its emission abatement and energy intensity reduction effects. Thus, future research should aim at exploring how the market failure for energy research and development, and cost of modern energy technologies hamper the adoption of green energy in developing countries. Such a study would be crucial in assessing clean and modern energy for all—as stipulated in the Sustainable Development Goal 7.

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