AEM JOURNAL .ORG

Clean Energy, Carbon Emissions, and Green Economic Transition in China

Jinwen Chen[1], Bingxue Wang[2]
[1]School of Economics, University of Sheffield, Sheffield S10 2TN, United Kingdom
[2]International College, University of Sheffield, Sheffield S1 4DF, United Kingdom
Corresponding author: Jinwen Chen (e-mail: chenjinwne221@gmail.com).

ABSTRACT China's continued expansion of clean energy makes it important to distinguish realized clean energy use from the physical deployment of renewable energy infrastructure. Within an energy–carbon–economy conceptual framework, this study examined whether greater clean energy development was associated with lower carbon emission intensity and a higher level of green economic transition, and whether physical photovoltaic deployment displayed the same regional pattern as realized clean energy consumption. Balanced panel data from 30 Chinese provinces for 2011–2023 were analyzed using two-way fixed effects models. Green economic transition was measured using the Global Malmquist–Luenberger green total factor productivity index. Potential channels through green technological innovation and industrial structure upgrading and differences across regional economic and resource conditions were also examined. Robustness was evaluated through sample exclusion, propensity score matching, and instrumental variable estimation. An extension combined remotely sensed photovoltaic deployment with surface solar radiation data for 2011–2022 to construct deployment-based and radiation-weighted indicators. The results showed that greater clean energy development was significantly associated with lower carbon emission intensity and a higher level of green economic transition, and these relationships remained robust. Green technological innovation and industrial structure upgrading provided evidence of possible transmission channels, while the estimated relationships differed across regional groups. However, the photovoltaic indicators did not reproduce the same lower-carbon and higher-green-transition pattern observed for consumption-based clean energy development. These results indicate that solar electromagnetic radiation conditions, photovoltaic infrastructure deployment, and realized clean energy utilization represent related but distinct stages of the energy transition. By linking remotely sensed photovoltaic conditions and solar radiation with regional environmental and economic outcomes, this study provides a system-level perspective connecting the physical foundations of photovoltaic energy conversion with low-carbon and green development.

INDEX TERMS clean energy development, carbon emissions, green economic transformation, photovoltaic deployment, solar electromagnetic radiation

I. INTRODUCTION

AMONG the most critical environmental problems facing humanity today are the changing global climate and the continuing increase in the production of greenhouse gases. According to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [1], the average temperature has risen by about 1.1°C across the entire planet since the beginning of the Industrial Revolution, largely due to high levels of emissions of carbon dioxide and other greenhouse gases. Fossil fuel consumption is the main contributor to global CO_2 emissions and has a long-term correlation with economic growth [2]. As a typical energy-dependent economy, South Africa's energy sector contributes about 15% of its economic output, and coal accounts for about 70% of its energy supply. Climate change has already led to significant impacts at the ecosystem level, such as changes in soil carbon storage and degradation of natural systems [3]. However, other researchers believe that economic development is the primary issue, so striving to balance environmental sustainability with economic growth has become a consensus. The global crisis has made the concepts of "world community with a common future for humankind" and "sustainable development" major issues in the international community, creating a new global consensus and a historical opportunity for the restructuring of energy and green cooperation between countries.

Energy plays a crucial role in human survival and socioeconomic progress and serves as the cornerstone of global development and the main driver of modern industry, transportation, and life. Notwithstanding the rapid growth of renewable energy (RE) in the past few years, petroleum and coal continue to dominate the world's energy framework. In 2020, petroleum and coal were more than 83% of the world's energy consumption, highlighting that these will remain an essential component of national energy frameworks in many countries [4], [5]. In developing economies like China, the dependence on fossil fuels is even more pronounced. On the one hand, coal still dominates China's energy structure, accounting for about 57% of its total primary energy consumption [6]. On the other hand, existing research shows that the carbon emission driving mechanisms are completely different in different regions, with carbon emission growth slowing down in high-income regions and a relative decoupling emerging. Meanwhile, low- and middle-income regions are still in the "high growth-high emissions" stage [7]. The search for clean, renewable alternatives has become a collective global dream towards achieving sustainable development.

Carbon dioxide (CO_2) is widely recognized as the major driver of global warming and climate change. There is no doubt that human activities have led to the warming of the atmosphere, oceans, and land, and that the basic cause of this is the excessive accumulation of GHG emissions [1]. Of these gases, the one with the greatest effect is CO_2, which accounts for around 74% of all greenhouse gas emissions globally [8]. The constant use of petroleum and coal for transport, electricity generation, and industrial production has led to the steady increase in the CO_2 concentrations of the atmosphere, which has had serious climatic consequences like sea level rise, extreme weather, and global warming. In China, over 90% of the total GHG emissions are from CO_2 [6], which further stresses the central role of fossil fuel combustion in the carbon emissions of the country. Yet, increasing the use of renewable energy is a viable way to combat climate change; The importance of the shift towards energy from renewable sources in reducing emissions as well as achieving global sustainable development [9].

In light of the major challenges that come with too much carbon emissions as well as continued reliance on fossil fuels, green energy has become an international trend in fighting climate change and realizing sustainable development. Under its accelerated transformation scenario, renewable energy is expected to meet about two-thirds of the world's energy demand by 2050. At the same time, the scholar pointed out that the core of the path to achieving this is the expansion of renewable energy and the improvement of energy efficiency [10]. Some scholars have studied the relationship between China's CO_2 emissions and economic growth, energy structure, and foreign trade. In the short term, they have emphasized that developing renewable energy is the key to medium and long-term emission reduction; in the long term, they have emphasized that renewable energy and foreign trade (openness) help reduce CO_2 emissions [11]. Other scholars have pointed out that the self-sufficient expansion of low-emission electricity can better achieve carbon emission reduction and economic growth; they also emphasized that while promoting the clean electricity revolution, it is important to avoid excessive regional disparities and to give preference to the central and western regions [12]. For China, the key to becoming carbon neutral is to speed up the transition towards clean energy and continue to grow the economy [13]. Hence, the reconciliation of the tension between economic growth and carbon reduction through understanding the role of clean energy has become a key issue not only for academic research but also for policymaking.

Experiences from developed economies have shown that stringent environmental regulations, in combination with technological innovation, can deliver compatibility between reducing emissions and economic growth. In Europe, the European Union Emissions Trading System (EU ETS) has been considered an innovative market-based mechanism which that been able to efficiently motivate companies to use cleaner technology as well as reduce emissions. In the United States, empirical evidence from studies of the Clean Air Act suggests that stringent regulatory efforts on pollutants have resulted in remarkable reductions in sulfur dioxide as well as other emissions, thus demonstrating that environmental quality can be improved via regulatory intervention without negatively affecting economic growth [14]. Experience in advanced economies indicates a virtuous cycle between regulation and innovation. For China, to build an effective and sustainable green transition framework, it is important to draw upon such institutional and policy lessons from developed countries [15].

China's resource framework is mainly reliant on carbon-intensive sources, with a remarkable dependence on coal for its economy. Fossil fuels make up over 85% of overall energy consumption and 92% of the cumulative CO_2 emissions in China, according to [6]. This shows low energy efficiency as well as high carbon intensity in the current energy system. China is a key participant in realizing global carbon reduction targets, accounting for about 27% of global GHG emissions as well as about one-third of fossil fuel–related CO_2 emissions, reaching nearly 11.9 gigatons in 2023 [16]. China has implemented a series of rigorous measures, and its pledge to reach peak carbon emissions by 2030 and realize carbon neutrality by 2060 mirrors a robust policy commitment. The fourteenth five-yearly plan clearly priorities the RE transition as well as green growth [17]. China has actively advanced clean energy development (CED) via policy support and investment initiatives, thus yielding preliminary results. China's national ETS, formally launched in July 2021, has become the world's largest carbon-market system by the amount of CO_2 emissions covered [18]. Meanwhile, the capacity of wind and solar energy increased quickly, and non-fossil energy's proportion of overall generation kept rising, reducing the pressure from power-sector carbon emissions [19]. In addition, the growth of RE has been greatly aided by green funding as well as policy support for China's low-carbon transition, thus providing essential financial and innovation incentives for sustainable growth [20]. Nevertheless, whether the expansion of CED simultaneously translates into lower carbon emission intensity (CEI) and improved green economic transformation (GET) remains an empirical question.

Existing studies provide important evidence on the relationships among renewable energy, carbon emissions, and green economic performance. However, several research gaps remain. Carbon emissions and green economic performance have frequently been examined separately, providing limited evidence on whether CED is associated with both lower CEI and higher GET within the same empirical framework. Evidence on the relevant transmission mechanisms remains fragmented, and the roles of green technological innovation (GTI) and industrial structure upgrading (ISU) have not been sufficiently evaluated together within the same framework. Conventional consumption-based CED indicators also provide limited information on the physical deployment and locally available energy resources of specific clean energy technologies. These limitations motivate an empirical analysis that combines environmental and economic outcomes, potential transmission channels, regional differences, and technology-specific spatial measures. Among clean energy technologies, solar photovoltaics (PV) provide a direct physical link between the energy transition and electromagnetics. Solar radiation constitutes broadband electromagnetic radiation. When incident photons are absorbed by semiconductor materials, electron–hole pairs are generated and subsequently separated by the internal electric field of the device, enabling electrical current to be collected. Electromagnetic research has further examined multifunctional structures that combine photovoltaic energy conversion with radio-frequency functions. For example, a compact meshed solar-cell antenna was developed to enable both photovoltaic energy harvesting and RF transmission [21]. This example illustrates that the utilization of solar energy is fundamentally associated with electromagnetic-wave absorption, photon–semiconductor interaction, and electrical-energy conversion.

At the regional level, however, the original consumption-based CED indicator cannot reveal the physical location of PV facilities or their spatial alignment with locally available solar-radiation resources. Optical satellite remote sensing provides a spatially explicit approach for observing PV infrastructure. Multisource satellite imagery, deep learning, and change-detection methods were used to map the spatial extent and installation years of PV power plants in China from 2010 to 2022 [22]. These considerations motivate the introduction of cumulative remotely sensed PV deployment density and radiation-weighted PV potential as technology-specific and spatially explicit extensions to the original CED indicator. This extension connects incident solar electromagnetic radiation, observed PV infrastructure deployment, and provincial environmental and economic outcomes, while complementing rather than replacing the original consumption-based measure. These indicators should be interpreted as relative spatial proxies for technology-specific deployment and radiation-resource alignment rather than as complete engineering estimates of actual PV electricity generation or device-level conversion performance.

Accordingly, this study addresses the following research questions: Is CED associated with lower CEI and higher GET? Do GTI and ISU serve as potential channels through which CED is associated with GET, and do the estimated relationships vary across regions? Are cumulative remotely sensed PV deployment density and radiation-weighted PV potential associated with provincial CEI and GET? These questions are examined using a balanced panel of 30 Chinese provinces from 2011 to 2023, while the PV analysis provides a technology-specific extension to the main CED analysis.

The innovation of this study lies in connecting several aspects of clean energy development that are often examined separately. CEI and GET, with GET measured by GTFP, are considered within the same provincial setting so that carbon performance and green economic performance can be assessed together. GTI and ISU are examined as potential channels, while differences in regional economic development levels and resource endowments are also considered. The study further extends the original consumption-based CED indicator by introducing cumulative remotely sensed PV deployment density and radiation-weighted PV potential. This measurement extension distinguishes realized clean energy consumption from the physical deployment of PV facilities and their spatial alignment with local solar-radiation resources.

The scientific contribution of this study is reflected in the empirical evidence on how different aspects of clean energy development are related to environmental and economic outcomes. The results show that a higher level of CED is associated with lower CEI and higher GET, indicating that changes in the energy consumption structure are related to both carbon emission reduction and improved green economic performance. The positive relationships of CED with GTI and ISU support their possible roles as transmission channels, while the subgroup estimates show different patterns across regions with different economic conditions and resource endowments. The PV extension does not identify the same favorable contemporaneous relationships for physical PV deployment and radiation-weighted PV potential. This difference indicates that available solar radiation, installed PV infrastructure, and effective clean energy utilization should not be treated as equivalent. Grid connection, renewable electricity utilization, fossil-energy substitution, and other supporting conditions need to be considered when explaining how the physical expansion of PV facilities may be translated into lower CEI and higher GET.

The remainder of this paper is organized as follows. The next section develops the theoretical framework and research hypotheses. The Methodology and Empirical Design sections describe the conceptual framework, data, variables, and empirical models. The Empirical Results and Discussion section reports the baseline results, robustness and endogeneity tests, potential transmission channels, regional heterogeneity, and the technology-specific PV extension. The final section presents the main conclusions, policy implications, limitations, and directions for future research.

II. THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

A. THEORETICAL BACKGROUND

Recent research has offered extensive empirical evidence on the elasticity in the context of energy consumption, greenhouse gas emissions and economic development, which reveals a complicated interaction that underpins the green transition. The stability of the 3E relationship has been examined, and it has been found that over time, carbon emissions' responsiveness to economic development has decreased, which suggests a potential decoupling between economic activity and environmental pressure [23]. When the proportion of energy generated from renewable sources exceeds a specific threshold, its elasticity effect on CO_2 mitigation becomes stronger [24]. This means that changes in the energy structure have a directional and scale effect on emissions reduction.

From a policy perspective, the elasticity of CO_2 emissions to carbon pricing is found to be that with a 1% increase in carbon price, the annual growth rate of CO_2 emissions can be reduced by around 1%, highlighting the effectiveness of market-based approaches in reducing emissions [25]. The expansion of renewable energy in the electricity sector leads to approximately a 7.4% reduction in CO_2 emissions one year later, highlighting the lagged but persistent environmental benefits of non-fossil energy deployment [26].

At the cross-country level, a dynamic panel model is used to analyze the relationship between different types of renewable energy and carbon intensity (CO_2 emissions per unit of GDP). Their findings show remarkable negative coefficients, which confirm that increased renewable energy adoption leads to a decrease in carbon intensity [27]. Lastly, Long-run evidence, which reduces the release of carbon dioxide by around 0.26% for every 1% increase in the use of RE, further stresses the cumulative and long-term effects of clean energy utilization [28].

All in all, the findings confirm that energy elasticity, carbon emission elasticity, and economic growth are deeply interlinked, which builds a significant theoretical foundation for the model framework of the research. Existing research shows that there is a two-way relationship between renewable energy investment and economic growth. However, in specific empirical studies, it is necessary to identify a benchmark path in the above two-way interaction to construct an empirical model. In the context of China's system, this paper chooses to regard the development of clean energy as the starting point for influencing the green economy, rather than being endogenously determined by economic prosperity. On the one hand, the development of clean energy in China is highly dependent on national policies. In the empirical study of China's panel data, it was found that the combined effect of renewable energy consumption and strict environmental policies significantly promotes economic growth and economic sustainability [29]. On the other hand, renewable energy investment may lag in the short term, but it will show a driving effect on economic growth in the long term [30]. It requires a period of technology diffusion and industrial structure adjustment to achieve certain economic results. Therefore, in the theoretical framework and empirical model, this paper takes the development of clean energy as the core explanatory variable, systematically examines its impact on carbon emission intensity and green economic transformation, and deals with potential endogeneity issues in the subsequent empirical analysis through the mediation effect model and instrumental variable method.

B. CLEAN ENERGY AND CARBON EMISSION REDUCTION (H1)

From the perspective of environmental economics as well as energy transition theory, CED has an important role to play in realizing the decoupling of economic growth from environmental degradation. Through the replacement of fossil fuels and encouraging technological innovation, RE enhances energy efficiency and contributes to a low-carbon transition, and therefore to a decrease in CEI.

Empirical research is consistent in affirming the negative elasticity. In the Chinese context, it is found that RE consumption remarkably curbs CO_2 emissions both in the short and long term [31], while a nonlinear negative elasticity between RE investment and emissions has also been identified [32]. Internationally, the elasticity of RE is shown to be higher for highly globalized economies [33] and possible threshold effects depending on the scale of investment [34]. These differences arise from variations in samples, measurement methods, and whether endogeneity is considered. While the literature generally agrees that increasing the utilization of renewable energy is an effective way to reduce carbon dioxide emissions, the strength and pathways of this effect remain context-dependent and require careful causal testing within specific national contexts. Based on the insights, the research proposes the following hypothesis:

H1: The development and utilization of clean (renewable) energy remarkably reduces CEI.

C. CLEAN ENERGY AND GREEN ECONOMIC TRANSFORMATION (H2)

The green economic transformation is not simply about pursuing economic expansion, but rather about emphasizing the systematic improvement of the quality and sustainability of economic growth under resource and environmental constraints [35]. The green economic transformation coordinates economic development and ecological environmental protection, reduces the country's dependence on natural resources and the environment, and promotes the economy towards high efficiency and low carbon. Just as the goal of the OECD is to achieve long-term economic prosperity rather than short-term growth at the expense of the environment, based on this characteristic, existing studies usually use comprehensive indicators to measure the level of green economic transformation in order to comprehensively reflect the performance of the economic system under environmental constraints. In the process of green economic transformation, the development of clean energy has become an important supporting factor for promoting the evolution of the economic system towards low carbon and sustainability. The expansion of clean energy can change the energy input structure and alleviate the resource and environmental constraints faced by economic growth. Existing studies have generally found in the empirical analysis of different countries and regions that energy transformation plays a key role in shaping the green growth path. For example, research on OECD national data shows that energy

transformation can improve the sustainability of the economic system while reducing environmental pressure and promoting the improvement of green growth level [36]. Similarly, empirical studies on emerging Asian economies have found a significant positive relationship between low-carbon energy transition and environmental investment and sustainable economic outcomes, indicating that clean energy development has an important overall promoting effect in driving green economic transformation

[37]. These studies provide strong support for the positive relationship between clean energy development and green economic transformation from a macro-empirical perspective.

Based on the above analysis, this paper proposes the following hypothesis:

H2: Clean energy development significantly promotes green economic transformation (measured by GTFP).

D. INNOVATION MECHANISM (H3A)

Technological innovation is extensively considered as a key channel through which clean energy drives green economic transformation. Consistent with the Porter Hypothesis, environmental regulation and clean-energy policies can stimulate firms' innovation incentives as well as offset compliance costs while clean-energy development accelerates industrial upgrading and efficiency improvements via technology spillovers.

Evidence supports the innovation-driven pathway. The dynamic interactions among renewable-energy technological innovation, environmental regulation intensity, and carbon pressure in China demonstrate that innovation is related to reductions in carbon pressure [38]. Using patent counts for 25 countries (1978–2003), it is found that public policy significantly boosted renewable energy patent applications, but the effectiveness of policy tools varied by technology [39]. Evidence shows that government subsidies remarkably promote green innovation in manufacturing firms, with R&D investment serving as a mediating channel [40].

At the macro level, it is found that renewable-energy innovation improves China's total-factor carbon productivity (TFCP), which suggests concurrent gains in efficiency as well as a reduction in emissions [41]. Taken together, technological progress mediates the connection between clean-energy development and sustainable economic growth.

H3a: CED promotes green economic transformation through fostering green technological innovation.

E. STRUCTURAL MECHANISM (H3B)

In addition to its direct role in lowering carbon emissions, clean energy also enables green economic transformation through speeding up industrial restructuring, as well as upgrading, as the economy shifts from being powered by fossil fuels to being powered by renewables, the structure of production changes accordingly. According to the theory of industrial transformation, optimizing the energy structure is to reallocate the resource endowment from energy-intensive, low-value-added industries to high-efficiency, low-carbon and technology-intensive industries, thus improving the sustainability of the overall economic growth.

The structural pathway is supported by empirical research. In a comparative analysis among Chinese provinces, it was discovered that regional development stages and openness (like FDI inflows) have a remarkable effect on environmental performance as well as emission trajectories [42]. This emphasizes the role of structural upgrading and factor reallocation in achieving low-carbon transformation. Similarly, industrial structure upgrading is a decisive factor in emission reduction and efficiency improvement [43]. A more rational and advanced industrial structure enhances the connection between clean energy utilization and low-carbon productivity to enhance green total factor productivity (GTFP) through resource reallocation. In summary, clean energy plays a role in green transformation not only through emission reduction, but also in industrial upgrading and optimization of the economic structure. Based on the above theoretical and empirical evidence, this study puts forward the following hypothesis:

H3b: Clean energy promotes green economic transformation through accelerating industrial upgrading and optimizing the financial structure.

F. RESEARCH LIMITATIONS AND INNOVATIONS OF THIS STUDY

In extensive research on the relationships among energy structure optimization, carbon emissions and economic growth, there are still several gaps.

(1) Limited research perspectives: Most research rely on linear or unidirectional causality frameworks, thus ignoring the dynamic feedback as well as endogenous balance among economic growth, energy structure and carbon policy. To bridge these gaps, this study constructs an "Energy-Carbon-Economy (ECE)" conceptual framework that organizes the potential links between clean energy development, technological progress, and structural transformation, and elucidates hypothetical pathways through which clean energy may influence carbon emissions and the green economic transition.

(2) Insufficient variable and mechanism identification: Previous works often use single indicators like GDP or carbon intensity, thus failing to capture the multidimensional quality of green growth. In addition, few research empirically examine the mediating roles of technological innovation, structural upgrading as well as energy efficiency. This study employs green total factor productivity (GTFP) as a comprehensive measure of green economic transformation, calculated using the DEA–Malmquist index with undesirable outputs, so as to capture sustainable growth quality beyond GDP or carbon intensity. Moreover, we explicitly test the transmission mechanisms by implementing a panel mediation framework to examine whether clean energy development affects green transformation through green technological innovation and industrial structure upgrading.

(3) Neglect of heterogeneity: Regional differences in economic development, resource endowment, and policy intensity are rarely considered, which limits understanding of spatial disparities as well as policy spillovers in China's energy transition. This study employs regional subgroup tests for heterogeneity analysis. Specifically, we estimate the impact of provinces with different levels of economic development and resource endowments (resource-rich versus non-resource-rich regions), and report subgroup-specific coefficients for CEI and GET. While we do not explicitly model spatial spillover effects, this evidence helps to reveal spatial disparities in China's energy transition and reinforces the policy implications of differentiated regional strategies.

Overall, the research deepens theoretical understanding of clean energy's systemic role in promoting green economic transformation and delivers practical policy insights for realizing China's dual-carbon goals as well as high-quality development.

III. METHODOLOGY

A. OVERALL FRAMEWORK OF THE ECE SYSTEM

Existing research typically discusses the relationship between energy use, economic growth, and environmental outcomes from a broader "3E" (Energy–Economy–Environment) perspective and has developed various comprehensive assessment tools for policy scenario analysis. Among these, E3ME, as a typical macroeconomic econometric comprehensive model, has been used to assess the short- to medium-term and even long-term economic and environmental impacts of energy and climate policies (Cambridge Econometrics, 2022).

Against this background, the "Energy–Carbon–Economy (ECE)" framework proposed in this paper is positioned as a conceptual framework. Its purpose is not to construct a feedback loop model in the sense of system dynamics, but rather to implement a set of testable empirical relationships from a 3E perspective, serving empirical research at the provincial level in China.

To translate the aforementioned conceptual framework into testable empirical relationships, this paper, in the subsequent empirical section, uses provincial panel data to estimate the overall impact of Clean Energy Development (CED) on Carbon Emission Intensity (CEI) and Green Transition Quality (GET, measured by GTFP), and further examines the transmission roles of Green Technology Innovation (GTI) and Industrial Structure Upgrading (ISU) in the "CED-GET" relationship. The empirical model uses a two-way fixed effects setting as a baseline to control for long-term regional structural differences and annual common shocks; the mechanism test employs a mediation framework to transform theoretical paths into observable relational chains. Model specification, variable construction, and robustness design will be elaborated in Chapters 4 and 5 respectively.

IV. EMPIRICAL DESIGN

A. DATA SOURCES AND SAMPLE

The research conducts an empirical analysis via panel data from 30 provinces, autonomous regions and municipalities in China (hereinafter, "provinces") over the period 2011–2023. The sample excludes the Tibet Autonomous Region and the Hong Kong, Macao and Taiwan regions because of substantial missing data in relevant energy as well as economic statistics. The data are mainly obtained from the China Energy Statistical Yearbook, the China Statistical Yearbook, the statistical yearbooks of each province and the National Economic Research Database (CNRDS). All variables are organized at the province-year level, yielding a balanced panel dataset comprising 30 provinces observed over 13 years, for a total of 390 observations. The time span of the sample is determined by considering data availability, the progress of clean energy policies and the critical stages of China's green transformation during the 12th to 14th Five-Year Plan periods, making sure strong timeliness as well as policy relevance. The data types and construction methods used in this study are consistent with the common settings of mainstream literature in related fields (provincial panel and authoritative databases), thus ensuring the comparability and reproducibility of the results. To complement, rather than replace, the consumption-based CED measure, this study introduces a technology-specific empirical extension examining whether remotely sensed PV deployment and the solar radiation available at PV locations are associated with CEI and GET. The extension combines the "PV Power Plants of China from 2010 to 2022" dataset [22], NASA POWER all-sky surface shortwave downward irradiance data, and Chinese provincial administrative boundary data. After these spatial data are matched with the original provincial panel, the extension covers 30 provinces from 2011 to 2022, yielding 360 province-year observations. The original 2011–2023 sample remains unchanged for the main analysis, while the restricted sample is used only for the technology-specific extension reported in Table 13.

B. VARIABLE SELECTION AND DEFINITION

1) Dependent Variables

The research aims to examine the dual impacts of CED on carbon emissions as well as green economic transformation. Accordingly, two core dependent variables are defined as follows.

Carbon Emission Intensity (CEI), a key dependent variable for testing Hypothesis H1, measures the efficiency of economic growth relative to carbon emissions. Following the conventional method in existing literature, CEI is defined as the amount of CO_2 emissions generated per unit of GDP, expressed as:

$$CEI_{it} = \frac{CO_{2it}}{GDP_{it}}$$

Where CEI_{it} denotes the CEI of province i in year t; CO_{2it} represents the total annual CO_2 emissions (10,000 tons) of each province, estimated based on fossil fuel consumption data reported in the China Energy Statistical Yearbook via the IPCC-recommended reference coefficient method; and GDP_{it} is the real gross regional product (100 million yuan) calculated at constant 2011 prices to eliminate price fluctuations, a lower CEI value indicates a smaller carbon cost of economic growth and a higher level of low-carbon development.

Green Economic Transformation (GET) is another core dependent variable used to test Hypothesis H2. To capture both energy efficiency and environmental performance, this study adopts Green Total Factor Productivity (GTFP) as a proxy for GET. Compared with single-dimensional indicators, GTFP provides a more comprehensive reflection of the quality and sustainability of economic growth under resource and environmental constraints.

In the specific estimation process, the DEA-Malmquist index approach is used via the incorporation of undesirable outputs into the traditional total factor productivity framework as well as treating the energy consumption as an essential input factor; The Global Malmquist–Luenberger (GML) index is then calculated to achieve the annual GTFP values for each province, which are accumulated with the base year as 2011. Data are mainly gathered from the China Energy Statistical Yearbook and provincial statistical yearbooks. A higher GTFP value indicates higher production efficiency under given resource and environmental constraints, which indicates more important progress in green economic transformation.

2) Mediating Variables

To expose the inner workings by which CED affects green economic transformation, the research proposes two central transmission pathways. It introduces the following mediating variables, namely

(1) Green Technological Innovation: The variable tests the innovation mechanism (H3a). It is measured by the logarithm of the number of patent applications filed each year in each province for green. This method is consistent with existing research on patent counting practices [39]. The data are achieved through China Research Data Services (CNRDS) platform, which identifies patents related to energy conservation as well as environmental protection according to a green classification system. A logarithmic transformation is used to reduce right skewness in the data. It is expected that CED stimulates demand for related technologies, thus promoting innovation as well as driving green economic transformation.

(2) Industrial Structure Upgrading: The variable tests the mechanism of structure (H3b). It is measured by means of a composite indicator based on the ratio of the share of the tertiary industry in regional GDP and share of the high-tech manufacturing revenue in total industrial revenue. The indicator captures both the trend of economic tertiarization and industrial upgrading towards high technology as well as value-added production. This research channel is supported by the literature, which highlights the role of economic and industrial structure in shaping the emissions-mitigation effect of renewable energy [24]. The data is taken from provincial statistical yearbooks. It is expected that CED promotes the growth of service and high-tech industries, optimizing industrial structure as well as facilitating green transition.

This method is consistent with existing research on patent counting practices.

3) Explanatory Variable

The core explanatory variable in the research is CED, which measures the actual progress of regional energy structure optimization as well as low-carbon transition. Following the mainstream literature, CED is represented by the share of renewable energy consumption in total regional energy consumption. Specifically, it is calculated as the ratio of the annual consumption of non-fossil energy sources, which include hydropower, wind power, solar power, as well as biomass energy (measured in tons of standard coal), to total energy consumption (also in tons of standard coal) for each province. The indicator mirrors the penetration and substitution effect of clean energy within the overall energy mix, in which a higher value indicates a cleaner regional energy structure. Some scholars define CED directly as the proportion of non-fossil energy consumption, explicitly including hydropower. This is because, under China's provincial statistical standards, the completeness of non-fossil energy data is superior to that of categorized energy data [44]. In China's provincial level "Energy Balance Sheet", end-use energy consumption is usually only broken down into "coal, oil, natural gas, electricity", etc., without further breaking down the source of electricity at the consumption end, such as whether it comes from hydropower, wind power or thermal power. All data are obtained from the China Energy Statistical Yearbook as well as provincial statistical yearbooks and are standardized via a unified electricity-to-heat conversion coefficient so as to ensure data consistency as well as comparability.

We acknowledge that large-scale hydropower projects may entail non-negligible ecological and social externalities (e.g., habitat loss and resettlement). The scholar considers water television as an important component of a clean energy system, reflecting its contribution to mitigating climate change nationwide [45]. However, from the perspective of mitigating climate change, hydropower shares the same zero-carbon emission characteristics as wind, solar, and biomass energy. When studying carbon emission intensity (CEI) and green transition, its contribution to carbon neutrality by replacing fossil fuels is a primary consideration.

4) Technology-Specific Photovoltaic Measures

In addition to the consumption-based CED measure, Table 13 introduces two technology-specific PV indicators as an empirical measurement extension. These indicators are not included in the baseline regressions but are used separately in place of CED to examine whether remotely observed PV deployment and radiation-weighted PV potential are associated with CEI and GET. The first indicator, the logarithm of cumulative remotely sensed PV deployment density (LnRSPV), measures the cumulative physical area of PV facilities identified by year t, normalized by provincial land area. The second indicator, the logarithm of radiation-weighted PV potential (LnRWPV), further combines the observed PV area with annual NASA POWER all-sky surface shortwave downward irradiance at the corresponding facility locations. LnRWPV should be understood as a relative proxy for the spatial correspondence between deployed PV infrastructure and locally available incident solar shortwave electromagnetic radiation. It is not a measure of actual electricity generation, photovoltaic conversion efficiency, or complete engineering generation potential. Although the indicator incorporates PV area and local solar-radiation conditions, it does not directly account for module conversion efficiency, panel tilt and orientation, environmental temperature, equipment degradation, system losses, grid-connection status, energy storage, or PV curtailment. Moreover, an installation year identified through remote sensing indicates the physical presence of a PV facility rather than its operational status or the effective substitution of fossil-based electricity. Accordingly, these indicators are used as a technology-specific measurement extension to complement CED and should not be interpreted as direct measures of realized electricity output or energy conversion.

5) Control Variables

To accurately identify the net effects of CED on carbon emissions as well as green economic transformation, the research controls for several key factors that may affect the dependent variables. The selection of control variables is based on established economic theories alongside relevant literature and includes the following:

Economic development level (EDL): measured by the logarithm of real GDP per capita, deflated to 2011 constant prices, to capture the scale as well as technological effects associated with different stages of economic growth.

Openness level (OPL): represented by the ratio of total imports as well as exports to regional GDP, which reflects potential technology spillovers and competitive effects from international trade and investment.

Population density (PD): expressed as the logarithm of the ratio between the total resident population at year-end and administrative land area, capturing the potential effect of population concentration on energy consumption as well as environmental pressure.

Urbanization level (URB): measured by the proportion of the urban population in the total population, which reflects the changes in production alongside consumption patterns associated with rural-to-urban migration and shifts in energy use.

Financial development level (FDL): proxied by the ratio of financial institution loan balances to regional GDP, controlling for differences in capital allocation efficiency and financial support for green investment.

Human capital level (HCL): represented by the proportion of higher education students to the total resident population, indicating regional labor quality and innovation capacity that may facilitate green transformation.

All raw data for these control variables are obtained from the corresponding years of the China Statistical Yearbook and provincial statistical yearbooks, ensuring consistency with the data sources of the core explanatory variable and forming a unified and complete dataset for subsequent empirical analysis.

C. MODEL DESIGN

1) Baseline Regression Model

To test research hypotheses H1 and H2, which examine the direct effects of CED on CEI and GET, a two-way fixed effects panel model is constructed as follows:

$$\frac{\mathrm{CEI}_{it}}{\mathrm{GET}_{it}} = \alpha_0 + \alpha_1 \mathrm{CED}_{it} + \alpha_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{1}$$

As defined in Equation (1), i and t denote province and year, respectively, and the dependent variable represents either CEI or GET. The core explanatory variable CED_{it} refers to the level of CED. X_{it} is a set of control variables, including economic development level (EDL), openness level (OPL), population density (PD), urbanization level (URB), financial development level (FDL), and human capital level (HCL). μ_i represents province fixed effects, which control for unobservable time-invariant regional characteristics; ν_t denotes time fixed effects, which control for macroeconomic shocks that affect all provinces simultaneously; and ε_{it} is the random error term. The coefficient α_1 is of primary interest, as it captures the net effect of CED on both CEI and green economic transformation.

2) Mediation Effect Model

To examine the mediating mechanisms through which CED influences green economic transformation—specifically via green technological innovation (H3a), industrial structure upgrading (H3b), this study follows the mediation testing procedure proposed in the literature [46] and constructs the following system of equations:

$$\mathrm{GTI}_{it} = \beta_0 + \beta_1 \mathrm{CED}_{it} + \beta_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{2}$$

$$\mathrm{ISU}_{it} = \gamma_0 + \gamma_1 \mathrm{CED}_{it} + \gamma_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{3}$$

3) Technology-Specific Extension Model

To complement the consumption-based CED measure and examine the relationship between technology-specific PV deployment and the two outcome variables, this study further constructs an extension of the baseline two-way fixed effects model as follows:

$$Y_{it} = \delta_1 \mathrm{PV}_{it} + \delta_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{4}$$

where Y_{it} represents either CEI or GET. PV_{it} is alternatively measured by the logarithm of cumulative remotely sensed PV deployment density (LnRSPV) and the logarithm of radiation-weighted PV potential (LnRWPV). The two indicators are introduced separately into the model rather than simultaneously. X_{it} contains the same control variables as the baseline model, including EDL, OPL, PD, URB, FDL, and HCL. Province fixed effects and year fixed effects are represented by μ_i and ν_t respectively, while ε_{it} is the random error term.

In these specifications, the aggregate CED variable is replaced by one of the two technology-specific PV indicators. Because the availability of the remotely sensed PV and solar-radiation data limits the extension sample to 2011–2022, Equation (4) is estimated using 360 province-year observations. The coefficient δ_1 captures the conditional within-province association between the corresponding PV indicator and CEI or GET. It should not be interpreted as a causal effect of PV deployment.

V. EMPIRICAL RESULTS AND DISCUSSION

A. DESCRIPTIVE STATISTICS

Based on the balanced panel data of 30 Chinese provinces from 2011 to 2023, the research conducts descriptive statistical analysis for all variables used and the results are displayed in Table 1. The sample includes a total of 390 observations, and the mean, standard deviation, minimum, median, and maximum values of each variable mirror the central tendency, dispersion, and distributional characteristics of the data.

Table 2 presents the descriptive statistics of the main variables used in this study. The mean value of CEI is 1.375, with a standard deviation of 0.888, showing substantial variation in CEI across provinces and over time. The mean value of GET is about 1, suggesting some progress in green transition. Yet, its relatively small standard deviation suggests that the level of green total factor productivity across provinces is relatively concentrated.

The mean value of green technological innovation (GTI) is low while its standard deviation is relatively large, which reflects that China's overall level of green patent activity is still limited and that remarkable regional disparities exist in green innovation performance.

The mean value of the core explanatory variable, CED, is 5.7%, with a large gap between the minimum and maximum values. This suggests that the overall share of clean energy consumption in China is still relatively low and that the development of clean energy across regions is highly uneven.

All control variables fall within reasonable statistical ranges and are generally consistent with empirical findings from existing researches, which provides a solid data basis for the later econometric analysis.

B. CORRELATION ANALYSIS

Table 3 reports the Pearson correlation matrix of all variables used in the research. The results show that the core explanatory variable, CED, is strongly and significantly negatively correlated with CEI at the 1% level (correlation coefficient = –0.428), and remarkably positively correlated with GET at the 1% level (correlation coefficient = 0.314). The findings

TABLE 1. Descriptive statistics of variables

Variable Type	Variable name	Variable symbols	Variable Definition	Data Source
Dependent Variable	Carbon emission intensity	CEI	Carbon emissions per unit of GDP	China Energy Statistical Yearbook, Provincial Statistical Yearbooks
	Green economic transformation	GET	Measured by the DEA–Malmquist index	China Energy Statistical Yearbook, Provincial Statistical Yearbooks
Mediating Variables	Green technology innovation	GTI	Number of green patents	CNRDS Database
	Industrial structure upgrading	ISU	A composite indicator combining the share of the tertiary industry and the share of high-tech manufacturing	Provincial Statistical Yearbooks
Explanatory variables	Clean energy development level	CED	Share of renewable energy consumption in total energy consumption	China Energy Statistical Yearbook, Provincial Statistical Yearbooks
Control variables	Economic development level	EDL	Logarithm of GDP per capita	Provincial Statistical Yearbooks
	Openness level	OPL	Ratio of total imports and exports to GDP	Provincial Statistical Yearbooks
	Population density	PD	Logarithm of population density (population per 10,000 km^2)	Provincial Statistical Yearbooks
	Urbanization level	URB	Share of urban population in total population	Provincial Statistical Yearbooks
	Financial development level	FDL	Ratio of financial institution loan balance to GDP	Provincial Statistical Yearbooks
	Human capital level	HCL	Ratio of higher-education students to total resident population	Provincial Statistical Yearbooks
Extension variable	Cumulative remotely sensed PV deployment density	LnRSPV	ln[1 + cumulative PV area per 10,000 km^2 of provincial land]	Chen et al. (2024); GADM v4.1
	Radiation-weighted PV potential	LnRWPV	ln[1 + incident solar-energy potential per 10,000 km^2 of provincial land]	Chen et al. (2024); NASA POWER; GADM v4.1

TABLE 2. Descriptive statistics of main variables ($N = 390$)

Var Name	Obs	Mean	SD	Min	Median	Max
CEI	390	1.375	0.888	0.034	1.163	4.984
GET	390	1.030	0.090	0.328	1.014	1.605
GTI	390	0.339	0.475	0.001	0.157	2.542
ISU	390	1.376	0.761	0.527	1.216	5.690
CED	390	0.057	0.021	0.002	0.055	0.127
EDL	390	10.903	0.470	9.682	10.867	12.207
OPL	390	0.270	0.277	0.008	0.146	1.464
PD	390	5.466	1.287	2.063	5.659	8.282
URB	390	0.599	0.133	0.000	0.592	0.896
FDL	390	1.536	0.446	0.671	1.467	2.774
HCL	390	0.021	0.006	0.008	0.021	0.044

deliver preliminary empirical support for research hypotheses H1 and H2. Among the mediating variables, CED is also positively and significantly correlated with GTI and ISU at the 1% significance level (correlation coefficients = 0.530 and 0.333, respectively).

In addition, most of the control variables are significantly correlated with both the dependent variables and the core explanatory variable, which aligns with general economic theory. The majority of the correlation coefficients are below 0.7 and combined with the results of the variance inflation factor (VIF) test, it can be concluded that the model does not suffer from serious multicollinearity problems, thereby ensuring the robustness and reliability of the baseline regression results.

C. VIF TEST FOR MULTICOLLINEARITY

Table 4 reports the results of the variance inflation factor (VIF) test, which is used to diagnose potential multicollinearity problems in the regression model. All variables have VIF values far below the critical threshold of 10. The maximum VIF value is 3.253 (for economic development level, EDL), and the minimum is 1.546 (for clean energy development level, CED), with an average VIF of 2.409. These results clearly indicate that no severe multicollinearity exists among the explanatory and control variables, confirming that the model specification is reasonable and that the regression estimates are both valid and stable.

D. BASELINE REGRESSION RESULTS

Table 5 presents the baseline regression results of the impact of CED on CEI and GET. Column (1) reports the results using CEI as the dependent variable. The coefficient of CED is significantly negative at the 5% level ($\alpha_1 = -3.5108$), which directly verifies Hypothesis H1. The finding shows that a rise in the share of clean energy consumption reduces carbon emissions per unit of GDP.

Column (2) shows the results with GET as the dependent variable. The coefficient of CED is significantly positive at the 1% level ($\alpha_1 = 1.1440$), which provides strong support for Hypothesis H2 and confirms that the development of clean energy remarkably promotes green economic transformation, as measured by green total factor productivity (GTFP).

For the control variables, economic development level (EDL) has a remarkable negative impact on CEI, which is consistent with the Environmental Kuznets Curve (EKC) hypothesis but the direct effect of economic development level on green transformation is not significant. The rise in openness level (OPL) has a positive effect on emission reduction but a mild inhibitory effect on green transformation, which may be attributed to China's trade structure in global value chains. Meanwhile, financial development level (FDL) also reduces CEI, which shows the role of green credit as well as financial instruments in promoting emission reduction. Overall, the baseline regression results robustly support the two core hypotheses of the research, laying a solid empirical foundation for the later mechanism and heterogeneity analyses.

Compared with the findings of [32], both studies employed CEI as the dependent variable and arrived at identical results. While this paper's model controls for fixed effects (FE), [32] controls for spatial spillovers. Though their pathways differ, their directions align, with [32] further corroborating this paper's conclusions. This study utilizes GTFP to address the limitations of [11], which employed CE.

E. ROBUSTNESS TESTS

1) Excluding Municipalities

Table 6 reports the robustness test results after excluding the four municipalities—Beijing, Tianjin, Shanghai, and Chongqing—from the sample. Columns (1) and (2) use CEI and GET as the dependent variables, respectively. The results show that after removing these municipalities, which may have unique political and economic characteristics, the coefficient of CED remains significant at the 10% and 1% levels, respectively, and the signs are consistent with those in the baseline regressions (negative for CEI and positive for GET).

TABLE 3. Pearson correlation matrix of main variables

	CEI	GET	GTI	ISU	CED	EDL	OPL	PD	URB	FDL	HCL
CEI	1										
GET	-0.189***	1									
GTI	-0.346***	0.343***	1								
ISU	-0.352***	0.170***	0.410***	1							
CED	-0.428***	0.314***	0.530***	0.333***	1						
EDL	-0.397***	0.412***	0.659***	0.483***	0.453***	1					
OPL	-0.361***	0.116**	0.522***	0.475***	0.352***	0.604***	1				
PD	-0.285***	0.207***	0.506***	0.305***	0.219***	0.505***	0.670***	1			
URB	-0.231***	0.178***	0.426***	0.437***	0.198***	0.699***	0.633***	0.431***	1		
FDL	-0.162***	0.206***	0.182***	0.547***	0.277***	0.450***	0.349***	0.0580	0.481***	1	
HCL	-0.183***	0.284***	0.147***	0.282***	-0.0160	0.536***	0.209***	0.392***	0.462***	0.355***	1

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 4. Variance inflation factor (VIF) test for multicollinearity

	VIF	1/VIF
EDL	3.253	.307
OPL	3.193	.313
URB	2.639	.379
PD	2.504	.399
HCL	2.051	.488
FDL	1.675	.597
CED	1.546	.647
Mean VIF	2.409	.

This finding indicates that the core conclusions CED significantly reduces CEI (supporting H1) and promotes green economic transformation (supporting H2)—are not driven by the inclusion of municipalities with special administrative status. The results confirm the robustness of the main findings. Although the magnitude and significance of some control variables change slightly compared to the full-sample results, these differences reflect regional heterogeneity and do not alter the fundamental relationships between the key variables.

This finding further corroborates the observations in [7] and [42] regarding provincial heterogeneity in emissions and policy implementation, aligning with this study's rationale for excluding municipalities directly under central government jurisdiction. Compared to the model in [11], which neither excluded administratively distinctive municipalities nor conducted robustness tests, the present results more reasonably account for variations in urban structure.

2) Replace PSM Model

Table 7 reports the results of the re-estimation using the PSM method based on a 1:1 nearest neighbor matching sample. Similar frameworks have been used to evaluate the effectiveness of China's clean energy-related policies, and the approach in this paper is consistent with existing research [47]. Columns (1) and (2) show that, after effectively controlling for sample selection bias, the coefficients of the core explanatory variable — the level of CED — remain significantly negative and positive at the 5% and 1% levels, respectively. This result is highly consistent with both the baseline regression and the robustness test that excludes municipalities, once again providing strong evidence that CED significantly reduces CEI (supporting Hypothesis H1) and promotes green economic transformation (supporting Hypothesis H2). Although the coefficients and significance levels of some control variables change in the matched sample, this precisely demonstrates the effectiveness of using the PSM method to control for confounding factors, while the stability of the core variable relationships further reinforces the reliability of the main conclusions of this study.

Methodologically, compared to [32], which employed provincial-level spatial panels in China for spatial regression analyses such as SDM/SEM, the PSM approach in this paper complements their spatial models by addressing inter-provincial heterogeneity. The directionality of results aligns with the conclusions of [11]. By employing PSM to eliminate sample selection bias, this study enhances the reliability of its estimations.

3) Excluding the Impact of the COVID-19 Pandemic

To minimize potential distortions caused by abnormal economic fluctuations during the COVID-19 pandemic, this study further removes the sample period corresponding to the pandemic peak years (2020–2022) and re-estimates the baseline model. Excluding 2020–2022 leaves a balanced panel of 30 provinces over 10 years (2011–2019 and 2023), yielding 300 observations. This factor was excluded because economic activity and energy use were hit unprecedentedly during the pandemic, which could undermine cross-year comparability. Table 8 presents the regression results after excluding the pandemic years. Columns (1) and (2) take CEI and GET as the dependent variables, respectively. The findings indicate that, once the exceptional pandemic period is excluded, the coefficients of the key explanatory variable CED remain statistically significant at the 5% and 1% levels, and the signs are consistent with those obtained from the baseline regression (negative for CEI and positive for GET). This means that the beneficial impacts of CED in reducing CEI (supporting H1) as well as promoting green economic transformation (supporting H2) are not fundamentally affected by the pandemic shock, thus further confirming the robustness of the research's conclusions. While some regions faced temporary interruption in energy consumption patterns and deceleration of economic growth during the pandemic, the long-term contribution of clean energy to low-carbon development and green transition is still manifested, which indicates its strategic importance for sustainable economic growth in China.

F. ENDOGENEITY TEST

To mitigate potential endogeneity issues arising from bidirectional causality or omitted variables, this study employs the IV approach for re-estimation. Following existing literature, regional river density is selected as an instrumental variable for CED. The validity of this instrument is supported by the following arguments: First, hydropower is a major component of renewable energy, and river density naturally determines hydropower potential. Therefore, it is highly correlated with the regional clean energy development level, satisfying the relevance condition. Second, river density is a geographical feature that has existed long before modern industrialization and has no CED direct causal relationship with the dependent variables CEI and GET, thus satisfying the exogeneity (exclusion restriction) requirement.

Table 9 presents the endogeneity test results based on the two-stage least squares (2SLS) estimation. Columns (1) and (3) report the first-stage regressions, where the coefficient of the instrumental variable (regional river density) is significantly negative at the 1% level. This result suggests that, during the sample period, regions historically rich in rivers and with earlier hydropower development experienced relatively slower subsequent growth in other clean energy forms, leading to a negative correlation between river density and the clean energy consumption ratio. Nevertheless, this does not affect the validity of the instrument.

Columns (2) and (4) show the second-stage regression results. After controlling for endogeneity, the coefficient of CED remains significantly negative at the 1% level in the CEI model and significantly positive at the 5% level in the GET model. These findings are consistent with the baseline regression results and provide further robust evidence for Hypotheses H1 and H2 that CED significantly reduces C and promotes green economic transformation. The instrument validity tests also support these results: the Anderson canonical correlation LM statistics are significant, rejecting the null hypothesis of under-identification; the Cragg–Donald Wald F statistics are greater than the critical value at the 10% maximal IV size, indicating that weak instrument bias is not a concern. Compared with the results of using instrumental variables (IV) to identify the elasticity of CO_2 with respect to carbon prices in [25], this paper reaffirms the

TABLE 5. Baseline regression results: Effects of CED on CEI and green economic transformation

VARIABLES	(1) CEI	(2) GET
CED	-3.5108**	1.1440***
	(-2.0966)	(3.0655)
EDL	-3.3692***	0.0387
	(-5.0557)	(0.5004)
OPL	0.8692**	-0.1882*
	(2.2914)	(-1.6725)
PD	2.0059*	0.1335
	(1.6975)	(0.7797)
URB	-0.1222	-0.0930***
	(-0.8728)	(-3.1751)
FDL	-0.5074***	0.0091
	(-3.3752)	(0.2353)
HCL	36.5945**	-1.0486
	(2.5898)	(-0.3098)
Constant	27.1763***	-0.0721
	(5.2693)	(-0.0652)
Observations	390	390
R-squared	0.817	0.332
Year	YES	YES
Pro	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 6. Robustness test results after excluding four municipalities (Beijing, Tianjin, Shanghai, and Chongqing)

VARIABLES	(1) CEI	(2) GET
CED	-3.8667*	-3.8667*
	(-1.8524)	(3.3127)
EDL	-3.3615***	0.1368*
	(-4.4080)	(1.9622)
OPL	0.5043	-0.3282
	(0.8094)	(-1.4312)
PD	2.0206	0.0809
	(1.4791)	(0.6346)
URB	-0.0138	-0.0618***
	(-0.0793)	(-2.9799)
FDL	-0.5686***	0.0072
	(-3.6600)	(0.1995)
HCL	36.1992*	-7.5256***
	(1.8290)	(-2.9586)
Constant	27.4873***	-0.7002
	(5.1748)	(-0.8736)
Observations	338	338
R-squared	0.806	0.376
Year	YES	YES
Pro	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 7. Robustness test results using the Anderson canon. corr. LM statistic PSM method

VARIABLES	(1) CEI	(2) GET
CED	-3.4600**	1.2470***
	(-2.4082)	(3.2010)
EDL	-2.9497***	-0.0451
	(-3.9353)	(-0.4069)
OPL	0.9225**	-0.2007
	(2.2645)	(-1.6253)
PD	3.3993**	0.0272
	(2.0762)	(0.0748)
URB	0.2600	-0.0373
	(1.0742)	(-0.6502)
FDL	-0.3249**	0.0236
	(-2.3243)	(0.4760)
HCL	24.2198*	0.3406
	(1.6546)	(0.0754)
Constant	14.0881	1.3334
	(1.4278)	(0.4916)
Observations	316	316
R-squared	0.769	0.318
Year	YES	YES
Pro	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

necessity of employing TV. Compared with [30], the structural approach adopted in this paper resolves reverse causality and addresses endogeneity more reliably. Overall, after addressing potential endogeneity, the main conclusions of this study remain valid and robust.

G. MEDIATION EFFECT TEST

Table 10 shows the results of the mediation effect test, which directly verifies the two transmission mechanisms proposed in this study and reveals their underlying theoretical logic.

In Column (1), the coefficient of CED on GTI is significantly positive at 5% level of significance ($\beta_1 = 4.5673$). This is consistent with the

TABLE 8. Robustness test results after excluding the COVID-19 pandemic period (2020–2022)

VARIABLES	(1) CEI	(2) GET
CED	-3.5108** (-2.0966)	1.1440*** (3.0655)
EDL	-3.3692*** (-5.0557)	0.0387 (0.5004)
OPL	0.8692** (2.2914)	-0.1882* (-1.6725)
PD	2.0059* (1.6975)	0.1335 (0.7797)
URB	-0.1222 (-0.8728)	-0.0930*** (-3.1751)
FDL	-0.5074*** (-3.3752)	0.0091 (0.2353)
HCL	36.5945** (2.5898)	-1.0486 (-0.3098)
Constant	27.1763*** (5.2693)	-0.0721 (-0.0652)
Observations	390	390
R-squared	0.817	0.332
Year	YES	YES
Pro	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 9. Endogeneity test results using the 2SLS instrumental variable approach

VARIABLES	(1) first CED	(2) second CEI	(1) first CED	(2) second GET
IV	-0.0168*** (-2.9755)		-0.0235*** (-4.2554)	
EDL	0.0113** (2.4660)	0.2889 (1.1805)	0.0187*** (4.1758)	0.0747*** (2.6872)
OPL	0.0221*** (2.8140)	-1.2748*** (-3.0900)	0.0278*** (3.7889)	-0.1170*** (-2.7980)
PD	0.0024** (2.0578)	0.0953* (1.7491)	0.0033*** (2.9804)	0.0094* (1.8045)
URB	-0.0262** (-2.5066)	0.3988 (0.7046)	-0.0381*** (-3.5544)	-0.0625 (-0.9640)
FDL	0.0029 (1.0704)	0.4236*** (3.0822)	0.0070*** (2.6334)	0.0140 (0.9777)
HCL	-1.0591*** (-4.6870)	-49.4274*** (-3.7358)	-1.6947*** (-8.0962)	2.5876 (1.3973)
CED		-28.9216*** (-4.6451)		1.7198** (2.5302)
Constant	-0.0737 (-1.6154)	0.0534 (0.0228)	-0.1286*** (-2.8891)	0.0996 (0.4202)
Anderson canon. corr. LM statistic	62.495		18.196	
Cragg–Donald Wald F statistic	36.866		18.108	
Observations	360	360	390	390
R-squared		0.226		0.263

t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 10. Mediation effect test results: The transmission mechanisms of CED

VARIABLES	(1) GTI	(2) ISU
CED	4.5673** (2.4867)	2.5200*** (2.7170)
EDL	0.2406 (1.5957)	-0.5566*** (-3.6272)
OPL	-1.0121*** (-4.5759)	-0.6033*** (-3.4946)
PD	0.8352* (1.8858)	-0.3577 (-0.8672)
URB	0.1371 (0.8172)	-0.2083 (-1.3211)
FDL	0.0852 (0.9527)	0.2044*** (2.6070)
HCL	-51.7880*** (-6.4966)	-14.6285* (-1.9406)
Constant	-5.9371** (-2.4579)	9.5433*** (4.2245)
Observations	390	390
R-squared	0.889	0.970
Year	YES	YES
Pro	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

findings of [39]. From a theoretical point of view, the development of the clean energy industry gives rise to new technological demand and market opportunities. According to the technology-push and demand-pull theories, this gives incentives to firms to invest more in R&D of, for example, energy conservation, emission reduction and renewable technologies. Meanwhile, improvements in clean energy infrastructure create an experimental space for the application of new technologies, which accelerates their diffusion and iteration. Through these channels, technological progress ultimately facilitates green economic transformation, which provides direct empirical support for Hypothesis H3a.

In Column (2), the coefficient of CED on ISU is significantly positive at the 1% level ($\gamma_1 = 2.5200$). The mechanism is accomplished principally via two channels. First, the substitution effect, whereby CED directly replaces traditional high carbon industries, lowers the share of energy intensive sectors; second, the cultivation effect, in which it promotes the development of new green industries (photovoltaic, wind, and other renewable manufacturing) as well as the associated R&D and producer services; Together, the processes push the industrial structure towards high technology and high value-added activities, which improves the efficiency of resource allocation and promote green transformation at the macro level. This is direct evidence for Hypothesis H3b. Compared to [42], which emphasizes the importance of industrial structure from the perspective of EKC and development level, this paper directly uses ISU empirical evidence to prove that industrial structure is an important mechanism.

H. HETEROGENEITY TESTS

1) Economic Development Level Heterogeneity

As shown in Table 11, the results indicate that the promoting effect of clean energy development (CED) on green economic transformation (GET) is stronger and more significant in provinces with a higher level of economic development. This finding can be explained by a number of factors. First, economically advanced regions tend to have more developed technological innovation systems and higher R&D intensity, which can absorb and spread clean technologies more quickly. Second, these areas have a higher level of industrial completeness and a higher proportion of high-tech industries and service industries, which improves the compatibility between clean energy development and green transformation. Third, the welldeveloped financial markets and higher local fiscal capacity enable these provinces to offer more effective financial and policy support for green financing, making clean energy investment more efficient. In contrast, less developed provinces often have constraints such as weak innovation capability, financial support, and reliance on resource or energy-intensive industries, which lessens the marginal impact of CED for emission reduction and green upgrading. Overall, the heterogeneity suggests that the benefits of clean energy development are not simply dependent on energy investment itself, but also on the regional context of innovation, industrial structure, and financial inclusiveness.

2) Resource-Based City Heterogeneity

The results in Table 12 demonstrate that the carbon reduction impact of CED is especially strong in resource-based provinces. This may be explained by the fact that the areas, traditionally dominated by coal, oil as well as other fossil energy industries, are under more pressure to realize national carbon reduction targets. Hence, governments in resource-based provinces are more likely to practice more stringent environmental regulation and invest more in clean energy substitution in the pursuit of industrial upgrading. Furthermore, as the provinces tend to have abundant energy infrastructure as well as skilled labor in energy-related industries, they are more suited to repurpose the assets to clean technologies. In contrast, in non-resource-based provinces, the green transformation effect of CED is also significant but more stable, which mirrors the continuous incorporation of clean energy into diversified economic activities rather than structural replacement. Overall, these findings suggest that although the resource-based provinces are faced with more significant challenges in terms of transformation, clean energy development offers them a critical pathway to realize both emission reduction and economic diversification.

3) Remote-Sensing PV Deployment and Radiation-Weighted Potential

Table 13 presents a technology-specific extension that integrates the "PV Power Plants of China from 2010 to 2022" dataset [22], surface shortwave solar-radiation data from NASA POWER, and provincial administrative boundaries from GADM v4.1 with the original provincial panel dataset. Based on the common temporal coverage of these data sources, the extension uses a balanced panel of 30 Chinese provinces from 2011 to 2022, yielding 360 province-year observations. Unlike the original CED indicator, which is constructed from the share of non-fossil energy in total energy consumption, the two newly introduced indicators—cumulative remotely sensed PV deployment density and radiation-weighted PV resource potential—capture, respectively, the physical spatial deployment of photovoltaic facilities and the surface downward shortwave electromagnetic radiation available at their observed locations. This analysis is intended to complement rather than replace the original consumption-based CED indicator by examining whether these more technology-specific and spatially explicit measures of photovoltaic deployment are associated with carbon emission intensity and green economic transformation. To maintain comparability with the baseline estimations, the analysis retains the original dependent and control variables and includes province and year fixed effects.

Columns (1) and (2) use the logarithm of cumulative remotely sensed photovoltaic (PV) deployment density as the core explanatory variable. Column (1) reports the estimation result with CEI as the dependent variable. The coefficient of cumulative PV deployment density is positive (0.2803) and is only marginally significant at the 10% level when heteroskedasticity-robust standard errors are used. This result should not be interpreted as evidence that an increase in PV deployment raises carbon emissions. Existing studies have shown that some regions in China with abundant solar resources and relatively high levels of installed PV capacity simultaneously face constraints related to grid connection, interregional electricity transmission, and renewable power consumption. Consequently, the physical expansion of PV facilities does not necessarily translate into the effective utilization of renewable electricity within the same period [48]. Similarly, previous research indicates that the carbon-reduction effect of renewable energy development may be constrained by renewable electricity curtailment and the insufficient substitution of renewable energy for fossil fuels within the existing energy consumption structure [49]. Furthermore, the carbon-reduction benefits of PV deployment may not materialize immediately. Evidence from China indicates that renewable energy consumption has a statistically significant negative effect on carbon emissions in the long run, whereas its short-run effect is not statistically significant [50]. Therefore, the result in Column (1) is more appropriately interpreted as indicating the absence of a robust contemporaneous relationship between observed PV deployment and CEI, rather than suggesting that the expansion of PV facilities increases carbon emissions. Column (2) reports the estimation result with GET as the dependent variable. The coefficient of cumulative PV deployment density is positive (0.0219) but statistically insignificant. Although the direction of the coefficient is consistent with the theoretical expectation that the expansion of PV infrastructure may facilitate green economic transformation, the estimation does not provide sufficient evidence that an increase in the physical area of PV facilities alone is associated with a measurable improvement in provincial GTFP. One possible explanation is that GET is a comprehensive performance measure that simultaneously incorporates economic output, resource inputs, and environmental costs, whereas remotely sensed PV area captures only the spatial deployment of clean energy infrastructure. The physical expansion of PV facilities may be translated into green productivity improvements only when the facilities are effectively connected to the power grid, generate and deliver electricity efficiently, substitute for fossil energy, and interact with regional technological progress and other enabling economic conditions. Evidence from provincial-level data in China indicates that renewable energy development has diminishing marginal benefits for GTFP and that its effects depend on regional conditions [51]. Specifically, the favorable effect is stronger in regions with more advanced economic, social, environmental protection, and technological conditions. Previous research also identifies a nonlinear relationship between energy consumption transition and GTFP, indicating that the transition has a positive effect only when it remains within an appropriate range and that emerging technologies are an important enabling condition for translating energy transition into green productivity gains [52]. Columns (3) and (4) further use the radiation-weighted photovoltaic (PV) potential index as an alternative measure of cumulative physical PV deployment density. This indicator combines the cumulative area of PV facilities identified through remote sensing with the NASA POWER all-sky surface shortwave downward radiation data for the corresponding locations and aggregates them into a relative province–year measure. Compared with the deployment density constructed solely from the physical area of PV facilities, the radiation-

TABLE 11. Heterogeneity test results by economic development level

VARIABLES	(1) High economic development level CEI	(2) Low economic development level CEI	(3) High economic development level GET	(4) Low economic development level GET
CED	-1.0837	-4.9592*	1.0752**	1.5371**
	(-1.3820)	(-1.8197)	(2.4485)	(2.0823)
EDL	-1.6629***	-4.6640***	-0.1646	0.2258*
	(-5.3868)	(-2.7218)	(-0.5487)	(1.6984)
OPL	0.7083**	-0.7048	-0.0430	0.0800
	(2.5123)	(-0.4402)	(-0.5612)	(0.2938)
PD	-1.5295*	4.2407*	-0.2314	-0.2395
	(-1.7391)	(1.8545)	(-0.4696)	(-1.0785)
URB	-0.0295	-0.1839	-0.1271***	-0.0696
	(-0.2560)	(-0.3429)	(-2.9522)	(-1.0119)
FDL	0.0787	-0.5128*	-0.0232	-0.0062
	(0.5704)	(-1.8082)	(-0.3092)	(-0.0889)
HCL	22.5493**	102.0172	6.7915	-14.2216*
	(1.9948)	(1.5653)	(0.8517)	(-1.8267)
Constant	28.1112***	28.9010**	4.2042	0.0363
	(4.9150)	(2.5772)	(0.8043)	(0.0265)
Observations	193	194	193	194
R-squared	0.977	0.741	0.361	0.387
Year	YES	YES	YES	YES
Pro	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 12. Heterogeneity test results by resource endowment type (resource-based vs. non-resource-based provinces)

VARIABLES	(1) Resource-based cities CEI	(2) Non-resource-based cities CEI	(3) Resource-based cities GET	(4) Non-resource-based cities GET
CED	-3.7414*	-1.4825	1.3559***	1.3667**
	(-1.6825)	(-0.9390)	(2.9934)	(2.3818)
EDL	-4.1978***	-0.9100***	0.0944	-0.2214
	(-3.8203)	(-2.6733)	(1.5058)	(-0.7135)
OPL	-0.5260	0.2350	-0.0680	-0.3195*
	(-0.3128)	(0.9543)	(-0.5521)	(-1.9502)
PD	3.7478*	1.5906**	-0.0032	0.4793
	(1.6571)	(2.0037)	(-0.0250)	(0.6423)
URB	-0.2134	-0.1491	-0.0417	-0.1324**
	(-0.5257)	(-1.0039)	(-0.9954)	(-2.2150)
FDL	-0.5779***	-0.0436	-0.0324	0.0891
	(-2.9140)	(-0.3192)	(-0.8777)	(0.7683)
HCL	23.7734	37.4266***	-7.4438***	12.9778
	(1.1730)	(3.0181)	(-2.7300)	(1.2664)
Constant	29.0641***	0.1174	0.1848	0.1364
	(3.4621)	(0.0178)	(0.2304)	(0.0257)
Observations	247	143	247	143
R-squared	0.768	0.950	0.346	0.370
Year	YES	YES	YES	YES
Pro	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 13. Remote-Sensing PV Deployment and Radiation-Weighted Potential

VARIABLES	(1) CEI	(2) GET	(3) CEI	(4) GET
Ln cumulative remotely sensed PV deployment density (LnRSPV)	0.2803*	0.0219		
	(1.8974)	(1.1368)		
Ln radiation-weighted PV potential (LnRWPV)			-0.0164	0.0051
			(-0.4620)	(0.5578)
Controls	YES	YES	YES	YES
Observations	360	360	360	360
R-squared	0.8131	0.2802	0.8071	0.2781
Year	YES	YES	YES	YES
Pro	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

weighted indicator further accounts for spatial differences in solar radiation resources across regions. It therefore captures the spatial alignment between deployed PV infrastructure and local incident shortwave solar electromagnetic radiation, rather than assuming that all PV facilities are exposed to identical solar resource conditions. The estimated coefficient of radiation-weighted PV potential is -0.0164 in the CEI model and 0.0051 in the GET model. Therefore, the findings do not identify a statistically significant contemporaneous relationship between radiation-weighted PV potential and either CEI or GET during the sample period, nor do they provide evidence of a direct or causal effect. It should be emphasized that the radiation-weighted indicator constructed in this study is a relative potential proxy rather than a complete engineering estimate of the actual electricity generation or technical power-generation potential of PV facilities. Although the indicator incorporates both the physical area of PV facilities and local shortwave solar radiation conditions, it does not directly account for PV module conversion efficiency, panel tilt and orientation, ambient temperature, equipment degradation, system losses, grid-connection status, or electricity curtailment. Therefore, the statistical insignificance of the estimates should not be interpreted as evidence that radiation-weighted PV potential has no effect on CEI or GET, nor can it be used to conclude that no direct or causal effect exists. A more appropriate interpretation is that, within the 2011–2022 provincial sample and the contemporaneous two-way fixed effects specification employed in this study, no statistically significant contemporaneous association is identified between radiation-weighted PV deployment and either CEI or GET. Its potential effects may be lagged, nonlinear, or conditional on other complementary energy-system factors. Although the estimated coefficients are not statistically significant, their signs are consistent with the theoretical expectations and highlight the need to consider multiple stages—including solar resource availability, photoelectric conversion, and power-system utilization—when linking the physical deployment of PV facilities to realized environmental and economic benefits. Therefore, the main contribution of this extension lies in broadening the technical and spatial measurement of clean energy deployment, rather than providing causal evidence of the effects of PV deployment on CEI or GET.

VI. CONCLUSION AND POLICY IMPLICATIONS

A. RESEARCH CONCLUSIONS

Based on balanced panel data from 30 Chinese provinces over the period 2011–2023, this study examines the relationships between CED and two main outcomes, CEI and GET. The baseline and 2SLS estimates consistently show that a higher level of CED is associated with lower CEI and higher GET. These findings support H1 and H2 and indicate that an increasing share of clean energy consumption is related not only to lower carbon emissions per unit of economic output but also to improved GTFP. Changes in the regional energy consumption structure may therefore contribute to carbon emission reduction and green economic performance at the same time. The mechanism analysis shows that CED is positively associated with GTI and ISU. These results are consistent with the pathways proposed in H3a and H3b and support the possible roles of technological innovation and industrial structure upgrading in the relationship between CED and GET. The subgroup estimates further show different patterns across regions. The negative relationship between CED and CEI is more evident in provinces with lower economic development levels and in resource-based provinces, whereas the positive relationship between CED and GET is observed in both economic-development groups and both resource-endowment groups. These findings indicate that regional differences should be interpreted separately for carbon emission reduction and green economic transformation.

The technology-specific PV extension presents a different pattern from the main CED analysis. Cumulative remotely sensed PV deployment density does not show the same favorable contemporaneous relationships with CEI and GET as the consumption-based CED indicator, while radiation-weighted PV potential is not significantly associated with either outcome. These results should not be interpreted as evidence that PV deployment increases carbon emissions or has no environmental benefits. Instead, they indicate that the physical deployment of PV facilities and their spatial alignment with local solar-radiation resources are not equivalent to the effective utilization of clean energy. The environmental and economic benefits of PV deployment may depend on whether the facilities are effectively connected to the power grid, used for electricity generation, and able to substitute for fossil energy.

B. SCIENTIFIC AND PRACTICAL SIGNIFICANCE

The scientific significance of this study lies in showing that clean energy development should be understood as a process involving energy-resource availability, infrastructure deployment, effective energy utilization, and environmental and economic outcomes. The main results show that consumption-based CED is associated with lower CEI and higher GET, while the technology-specific PV indicators do not present the same favorable contemporaneous relationships. This difference extends the existing understanding of clean energy transition by showing that available solar-radiation resources, the physical deployment of PV facilities, and the realized consumption of clean energy represent different stages of the energy-conversion and utilization process. These stages cannot be treated as equivalent when evaluating the environmental and economic effects of clean energy. The findings for GTI and ISU further suggest that technological innovation and industrial structure upgrading may provide important supporting conditions for translating CED into improved green economic performance.

The practical significance of these findings is that the progress of clean energy transition should not be evaluated only by the physical scale of renewable energy infrastructure. Installed PV area and favorable solar-radiation conditions may not produce immediate carbon-reduction or green-productivity benefits unless the facilities are effectively connected to the power grid, generate and deliver electricity, and substitute for fossil-energy consumption. The findings therefore support a shift from an expansion-oriented approach to a utilization-oriented approach in the evaluation of clean energy development. Greater attention should be given to coordination among renewable energy investment, grid integration, energy storage, electricity consumption, technological innovation, and industrial upgrading. The regional results also indicate that the same clean energy strategy may produce different outcomes under different economic and resource conditions, providing a practical basis for more differentiated regional transition policies.

C. POLICY IMPLICATIONS

National energy policy should continue to increase the effective share of clean energy in total energy consumption. The negative relationship between CED and CEI and the positive relationship between CED and GET indicate that changes in the energy consumption structure may support carbon reduction and green economic performance at the same time. However, policy evaluation should consider not only the construction scale or installed capacity of clean energy facilities but also whether clean energy is actually generated, delivered, consumed, and used to substitute for fossil energy. Investment in power-grid upgrading, cross-regional electricity transmission, energy storage, and renewable electricity consumption should therefore develop together with the expansion of clean energy capacity.

The relationships of CED with GTI and ISU suggest that clean energy policy should be coordinated with technological and industrial policies. Governments can provide stable support for green R&D, encourage the application and commercialization of green patents, and promote the development of high-technology manufacturing and related service industries. Green finance and public investment can also be used to reduce the financing constraints faced by clean energy and green technology projects. These supporting measures may help convert clean energy development into technological progress, industrial upgrading, and improved green economic performance.

Regional clean energy policies should reflect differences in economic development and resource endowments. The relationship between CED and lower CEI is more evident in provinces with lower economic development levels and in resource-based provinces, indicating that these regions may have greater potential for carbon reduction through clean energy substitution. Resource-based provinces should accelerate the replacement of traditional fossil-energy industries and improve the use of existing energy infrastructure for clean energy development. Economically developed provinces can make greater use of their technological, financial, and industrial advantages to improve the efficiency and quality of clean energy utilization. Because the positive relationship between CED and GET is observed across different regional groups, support for green economic transformation should not be limited to economically advanced regions. The PV extension further suggests that the monitoring and evaluation of clean energy projects should combine spatial deployment information with actual operational indicators. Remotely sensed PV area and local solar-radiation conditions provide useful information on infrastructure deployment and resource availability, but they cannot directly reflect electricity generation, conversion efficiency, grid-connection status, curtailment, storage, or fossil-energy substitution. A more complete evaluation system should therefore combine remote-sensing and solar-radiation data with actual generation, grid operation, electricity consumption, and carbon-reduction data. This would help identify the gap between PV infrastructure deployment and effective energy utilization and support better coordination between clean energy engineering and regional transition policies.

D. CONTRIBUTIONS, LIMITATIONS, AND FUTURE RESEARCH

This study contributes to the existing literature by integrating CED, CEI, and GET into an ECE framework and examining the possible roles of GTI and ISU and the different regional patterns within the same empirical analysis. Rather than proposing a new economic or electromagnetic theory, the study provides an integrated perspective for understanding how changes in the energy structure are associated with both environmental performance and the quality of economic growth. The extension using remotely sensed PV deployment and solar radiation data further distinguishes solar resource availability, infrastructure deployment, effective clean energy utilization, and observed environmental and economic outcomes as related but different stages of the energy transition. This distinction provides a useful basis for connecting the economic analysis of clean energy with research on solar electromagnetic radiation, PV conversion, and energy-system performance.

Several limitations should be acknowledged. The provincial data used in this study cannot fully reveal the behavior of individual firms, power plants, or PV projects. The CED indicator also combines different non-fossil energy sources and therefore cannot separately identify the effects of solar, wind, hydropower, and other clean energy technologies. In addition, the results for GTI and ISU provide evidence of possible channels, but the present analysis does not estimate their complete indirect effects. The regional results describe different estimated patterns across provincial groups, while spatial spillovers and formal differences between all groups require further examination. Moreover, LnRSPV and LnRWPV are relative spatial indicators rather than direct measures of PV electricity generation or conversion efficiency. They do not fully capture module efficiency, grid connection, energy storage, power losses, or curtailment. The PV results should therefore be understood as contemporaneous associations rather than causal effects. Future research can extend this study by using city-, firm-, power-plant-, or project-level data and by distinguishing among different clean energy technologies. More complete channel tests and stronger identification methods can be used to examine the causal effects of CED, while spatial, nonlinear, and dynamic models can identify regional spillovers, threshold effects, and time lags. For PV research, remotely sensed deployment and solar radiation data can be combined with actual power generation, conversion efficiency, grid integration, storage, and curtailment information. Further interdisciplinary research may also link device-level factors—including spectral absorption, photon-to-electricity conversion, power losses, and reliability under different electromagnetic radiation conditions—to regional energy utilization and environmental and economic outcomes. Such research would provide a clearer understanding of how progress in electromagnetics, photonics, and PV technologies is translated into actual carbon-reduction and green-development benefits.

AUTHOR CONTRIBUTIONS

Chen J. designed, collected and analyzed the data, and drafted the manuscript. Wang B. conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Chen J. and Wang B. participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

No conflict of interest.

FUNDING

This research received no external funding.

ACKNOWLEDGEMENTS

The author thanks the handling editor and anonymous reviewers for valuable comments.

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