

Article

The Decoupling Relationship Evolution, Spillover Effects, and Characteristic Trends Between Renewable Electricity Generation and Carbon Emission Intensity in China

Jingyuan Li ^{1,2}, Yingchen Ge ^{3,4,*}, Shuke Fu ^{3,5} , Jiachao Peng ^{3,5,6,7} , Jiali Tian ^{3,5} and Meina Liu ³ 

¹ School of Management, Wuhan Institute of Technology, Wuhan 430205, China; 12006010001@stu.wit.edu.cn

² School of Economics, Wuhan Business University, Wuhan 430056, China

³ School of Law and Business, Wuhan Institute of Technology, Wuhan 430205, China; sk@wit.edu.cn (S.F.); jiachao.peng@wit.edu.cn (J.P.); tjli@wit.edu.cn (J.T.); lmn8276@gmail.com (M.L.)

⁴ School of Accountancy, Economics and Finance, Massey University, Palmerston North 4472, New Zealand

⁵ Center for High Quality Collaborative Development of Resources, Environment and Economy, Wuhan Institute of Technology, Wuhan 430205, China

⁶ Chinese Academy of International Trade and Economic Cooperation, Beijing 100710, China

⁷ School of Business Administration, Zhejiang Gongshang University, Hangzhou 310018, China

* Correspondence: yge@massey.ac.nz

Abstract

Against the backdrop of China's strategic goals of achieving carbon peaking and carbon neutrality, a key question is whether renewable electricity generation (REG) is associated with lower carbon emission intensity (CEI). To address this issue, this study employs panel data from 30 Chinese provinces from 2005 to 2024 and combines the Tapio decoupling model, Moran's I test, and the spatial Durbin model (SDM), with the ordinary least squares (OLS) used as a benchmark to analyze the decoupling evolution, spatial spillover associations, and potential transmission channels between REG and CEI. The findings show that: (1) the relationship between REG and CEI evolves from weak decoupling to strong decoupling, suggesting a potentially nonlinear relationship; (2) CEI exhibits significant spatial autocorrelation and regional clustering; (3) REG is significantly associated with lower CEI, with both local and spatial spillover associations; (4) the local mitigation association is stronger in eastern and higher-CEI provinces, while spillover effects are more pronounced in western, northeastern, and resource-based provinces; and (5) the REG-CEI association may operate through energy structure (ES) optimization and energy intensity (EI) reduction, while environmental regulation (ER) may strengthen this association. The endogeneity tests provide supplementary evidence consistent with these findings, although they should not be interpreted as definitive causal proof. Overall, this study contributes to the sustainability literature by showing that the REG-CEI relationship is not merely a static local association, but a dynamic and spatially differentiated pattern shaped by regional coordination and energy-system adjustment. These findings provide evidence relevant to sustainability-oriented energy policy by suggesting that renewable electricity development should be assessed not only by generation scale, but also by its association with carbon-intensity reduction, spatial coordination, and energy-system efficiency.

Keywords: renewable electricity generation; carbon emission intensity; spatial Durbin model; spatial spillover effect; decoupling relationship; regional heterogeneity



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1. Introduction

Achieving carbon peaking and carbon neutrality has become a central policy objective for China, requiring a fundamental transformation of the energy system. As the largest energy consumer and carbon emitter in the world, China faces increasing pressure to decouple economic growth from carbon emissions while maintaining sustainable development [1,2]. In response, the Chinese government has introduced a series of measures to reduce fossil-fuel dependence, promote clean energy development, and improve energy efficiency. These policies have accelerated the expansion of renewable energy and supported the transition toward a cleaner energy system. However, China's total carbon emissions remain high, even though carbon emission intensity (CEI) has declined over time (as shown in Figures 1 and A1 in Appendix B). This contrast suggests that carbon intensity, rather than total emissions alone, provides an important perspective for understanding whether economic growth is becoming less carbon-intensive under the low-carbon transition.

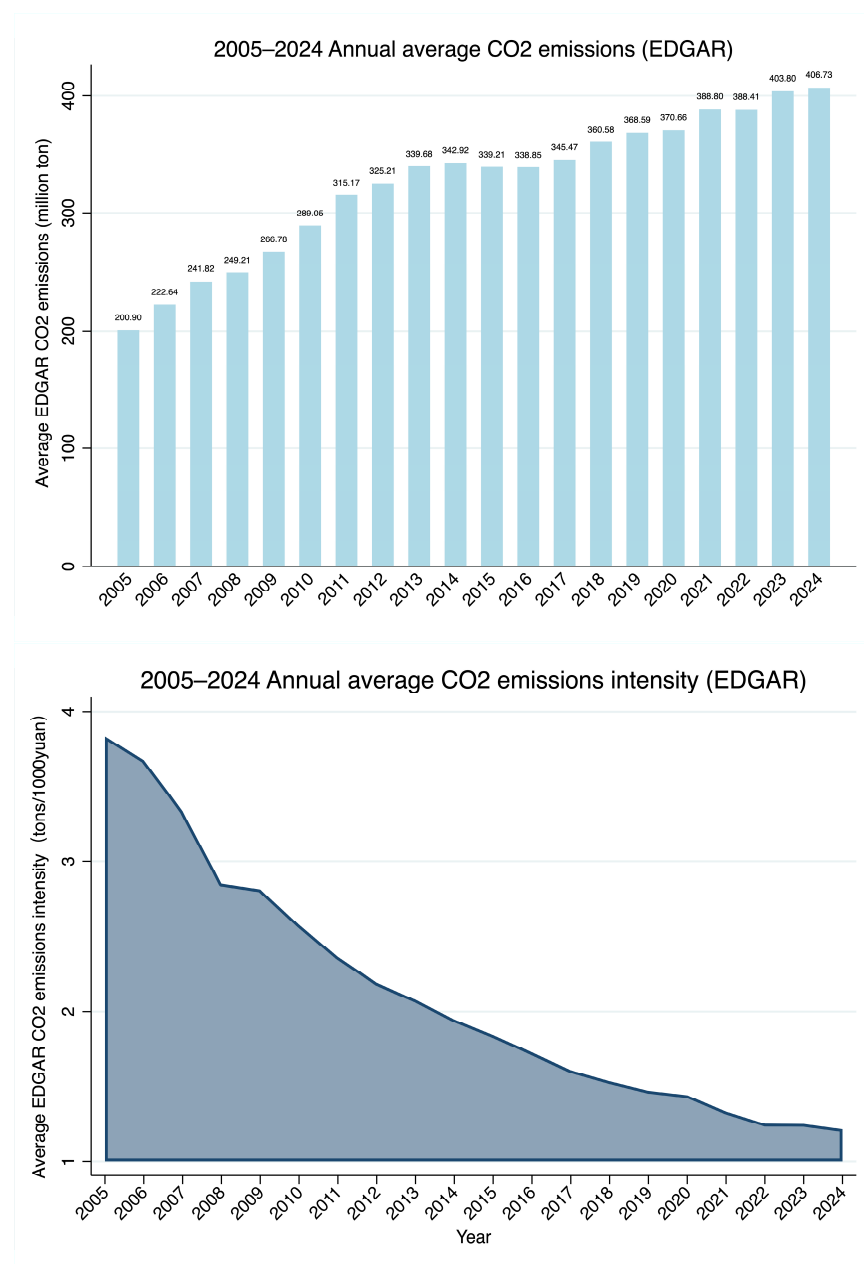


Figure 1. Annual average of carbon emissions and carbon emission intensity (CEI), 2005–2024.

Renewable electricity generation (REG) is widely regarded as a key pathway for mitigating carbon emissions and supporting the energy transition [3,4]. In China, REG has expanded rapidly in recent years (as shown in Figure 2), driven by the growth of hydropower, wind power, and solar power. Nevertheless, the expansion of renewable electricity does not automatically translate into proportional carbon mitigation. The carbon-intensity association of REG may depend on whether renewable electricity can effectively substitute fossil-based electricity, whether it can be absorbed by the grid, and whether electricity can be transmitted from resource-abundant provinces to high-demand regions. These issues are particularly important in China, where renewable resources, electricity demand, industrial structure, and grid transmission capacity are unevenly distributed across provinces. Therefore, it is necessary to examine not only whether REG is associated with lower CEI, but also how this relationship evolves over time and operates across space.

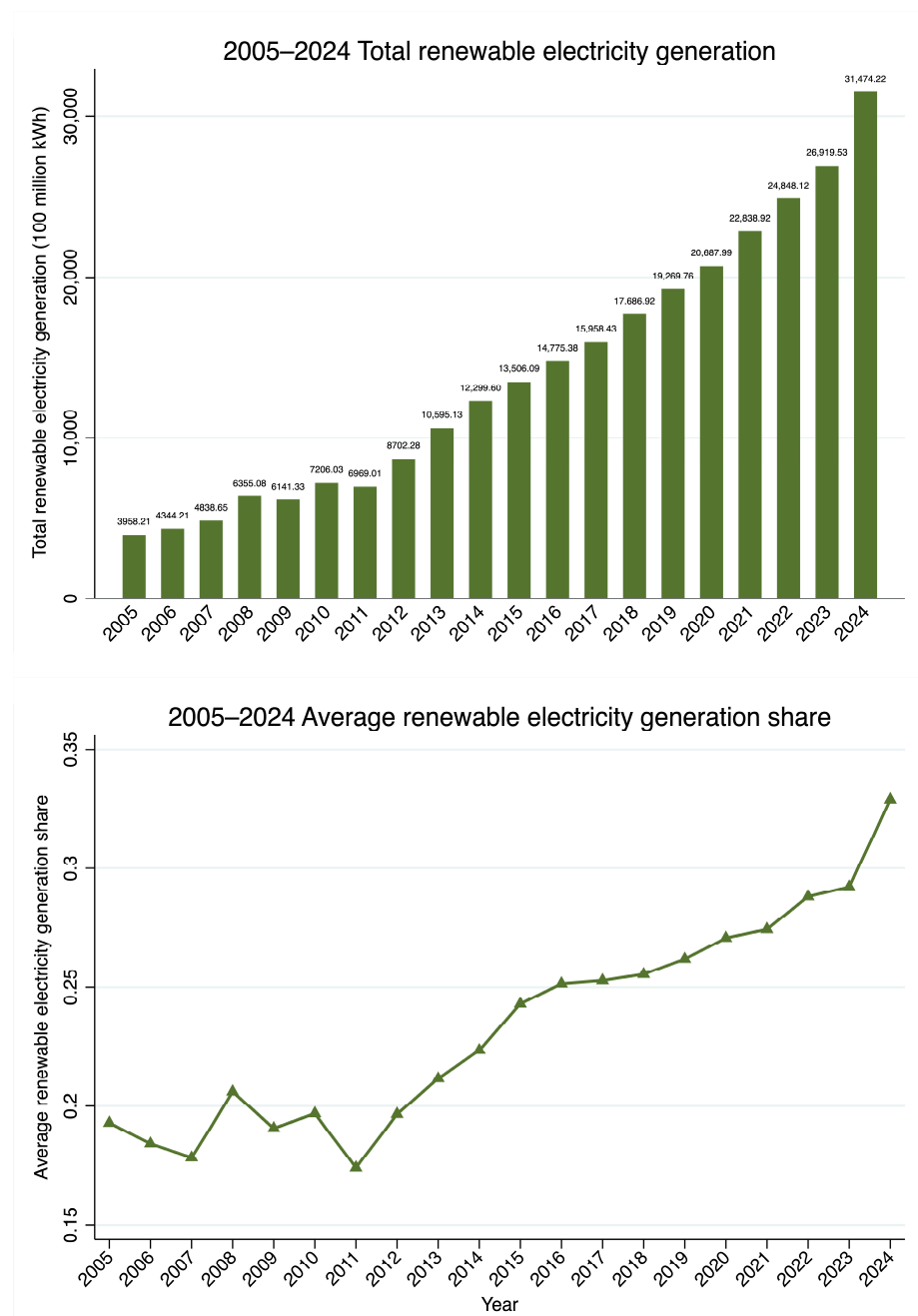


Figure 2. Renewable electricity generation (REG) (total and share) trend, 2005–2024.

Existing studies have examined renewable energy development and carbon emissions from different perspectives, but several gaps remain. First, many studies focus on the static relationship between renewable energy and emissions, while less attention has been paid to the dynamic [5] and decoupling relationship [6,7] between REG and CEI. Second, existing research often examines either spatial spillovers [3] or decoupling relationships [6,7] separately, making it difficult to understand whether the role of REG is purely local or spatially transmitted. Third, studies based on national averages may overlook regional heterogeneity, especially differences between resource-abundant and high-demand provinces. Fourth, although energy structure (ES) [8,9] and energy intensity (EI) [3,10] have been discussed as important channels, relatively limited evidence jointly examines these mechanisms together with the moderating role of environmental regulation (ER). Finally, some prior studies rely on relatively limited data periods or a single measure of REG or CEI, which may restrict their ability to capture recent changes in China's renewable electricity development and carbon intensity dynamics [3,11].

Against this background, this study provides an integrated analysis of the relationship between REG and CEI in China. Using panel data from 30 provinces over the period 2005 to 2024, this study first applies the Tapio decoupling model to examine whether the REG-CEI relationship has shifted over time as renewable electricity has expanded. It then uses Moran's I and the spatial Durbin model (SDM) to examine whether the REG-CEI association is confined to local provinces or extends across neighboring regions. Further analyses examine robustness, endogeneity, regional heterogeneity, and potential transmission channels through ES, EI, and ER. Rather than treating renewable electricity development as a single national average association, this design allows the study to describe how the REG-CEI relationship evolves dynamically, operates spatially, differs across provincial contexts, and is consistent with possible energy-system adjustment channels.

This study contributes to the literature in three main ways. First, it moves beyond a static average assessment of renewable electricity and carbon outcomes by showing that the REG-CEI relationship evolves from weak decoupling toward strong decoupling during 2005–2024. This provides new evidence that the carbon-intensity relevance of renewable electricity should be understood as an evolving transition pattern rather than a fixed average association. Second, it links decoupling analysis with spatial econometric evidence and shows that the REG-CEI relationship contains both local mitigation associations and cross-regional spillover associations. This distinction is important because renewable electricity generation, electricity consumption, and carbon-intensive production are spatially uneven across China, meaning that the CEI relevance of REG cannot be fully assessed within provincial boundaries alone. Third, it provides a differentiated explanation of the REG-CEI relationship by jointly considering regional heterogeneity, resource endowments, high- and low-CEI provinces, and evidence consistent with possible channels through ES, EI, and ER. These findings suggest that renewable electricity development should not be evaluated only by generation scale or installed capacity, but also by whether it is associated with lower CEI, spatial coordination, energy-structure optimization, energy-efficiency improvement, and environmental regulation. More broadly, the study strengthens the link between energy economics and sustainability by providing evidence on how renewable electricity development is related to sustainable low-carbon transition through dynamic decoupling, spatial coordination, and energy-system adjustment.

The results show that the relationship between REG and CEI evolves from weak decoupling to strong decoupling over the sample period. CEI exhibits significant spatial clustering, and the SDM results indicate that REG is significantly associated with lower CEI, with both local and spatial spillover associations. Further analyses suggest that this association is heterogeneous across regions and is more pronounced in eastern and

higher-CEI provinces, while spatial spillovers are stronger in western, northeastern, and resource-based provinces. Mechanism analysis provides evidence consistent with the roles of ES optimization, EI reduction, and ER in shaping the REG-CEI relationship.

The remainder of this paper is organized as follows. Section 2 reviews the related literature and develops the research hypotheses. Section 3 describes the data, variable construction, and empirical strategy. Section 4 presents the empirical results, including descriptive analysis, baseline SDM estimates, robustness checks, endogeneity tests, heterogeneity analysis, and mechanism analysis. Section 5 discusses policy implications and limitations. The Appendices provide supplementary formulas, figures, model specifications, and empirical results.

2. Literature Review and Hypothesis Development

This section develops the theoretical foundation and research hypotheses of this study. It first reviews the relationship between REG and CEI, with particular attention to local mitigation associations and potential spatial spillover patterns. It then discusses the moderating role of ER and the possible transmission channels through ES and EI. Based on these theoretical discussions, four hypotheses are proposed to guide the subsequent empirical analysis.

2.1. Renewable Electricity Generation and Carbon Emission Intensity

A large body of the literature has examined the relationship between REG and carbon emissions globally [12–14]. Existing studies largely focus on the determinants and impacts of renewable electricity generation. Empirical evidence indicates that factors such as renewable electricity policies [15], green finance development [16], energy intensity targets [17], and natural resource endowments [18] can promote REG, thereby enhancing economic welfare [19] and fostering economic growth [20]. Meanwhile, research on CEI primarily concentrates on its driving factors, including industrial structure adjustment or tertiary industry development [21,22], new quality productivity [23], foreign direct investment [4], and green technological innovation [24].

From a theoretical perspective, renewable energy is characterized by low carbon intensity and can generate clean electricity, thereby enabling green energy consumption and supporting carbon-emission mitigation [12,25,26]. According to energy system theory, including the energy production service system, energy consumption system, energy–environment system, and the 3E (Energy–Economy–Environment) framework [27], renewable energy plays a dual role in both energy production and energy consumption processes. Specifically, renewable energy sources such as wind and solar may generate certain carbon emissions during the construction phase of power generation facilities, but once operational, they provide electricity for end-users, thereby capturing both the production and utilization of clean energy within the energy system. In this sense, the construction and generation processes correspond to energy input and clean electricity output, jointly shaping their overall association with carbon emissions.

From a macro perspective, CEI reflects the coupling relationship between economic growth and carbon emissions, and the transition toward low-carbon energy is widely viewed as an important driver of this decoupling process [20,28]. Specifically, REG may be associated with lower emissions through multiple channels. First, from the supply side, by weakening the dependence of economic growth on fossil fuels, particularly coal [29], renewable energy may be associated with lower carbon intensity of energy generation, promoting a decoupling between economic activity and carbon emissions [18,30]. Furthermore, renewable energy provides low- or zero-carbon heat through direct use (e.g., solar, biomass, and geothermal), which may further be associated with lower carbon emissions [11]. Second,

from the consumption stage, renewable electricity enables the electrification of end-use sectors such as transportation, industry, and buildings, which is likely to be associated with lower emissions [11]. Finally, through the process of industrial transition, the expansion of renewable energy may reshape industrial structure by reallocating resources toward low-carbon sectors and technologies, thus facilitating a structural transition toward cleaner production systems [31]. Accordingly, REG is expected to be associated with lower CEI at the local level.

However, recent studies suggest that the estimated association of renewable energy is not confined to local regions but may also exhibit spatial spillover associations [3,32]. Due to substantial regional differences in resource endowments across China, renewable energy is often generated in resource-abundant regions and transmitted to other regions through interprovincial electricity grids (e.g., west-to-east power transmission). In addition, interregional economic linkages, energy trade, and technological diffusion allow renewable energy development in one region to influence carbon emission outcomes in other regions [33,34]. Therefore, REG may be associated with lower CEI not only locally but also in adjacent regions, reinforcing the spatial interdependence of emission reduction processes.

Hypothesis 1 (H1). *Renewable electricity generation is associated with lower carbon emission intensity and may exhibit spatial spillover effects.*

2.2. Moderating Role of Environmental Regulation

ER may condition the REG–CEI association. Existing studies show that ER is associated with pollution governance and emission-mitigation outcomes by increasing the cost of pollution-intensive activities and encouraging cleaner production [35,36]. More importantly, ER may also condition the carbon-related association of energy consumption, as stronger regulation has been found to weaken the carbon-enhancing effect of energy consumption in China [37]. In addition, recent evidence suggests that ER can promote renewable energy consumption and support clean energy transition [38]. Building on these findings, this study argues that stronger ER may strengthen the negative REG–CEI association by increasing the pressure to substitute fossil-based electricity with cleaner electricity and improving the implementation conditions of renewable energy policies. Therefore, ER is expected to strengthen the negative REG–CEI association.

Hypothesis 2 (H2). *Environmental regulation may strengthen the negative association between REG and CEI.*

2.3. Mediating Role of Energy Structure

The REG–CEI association may operate through changes in the ES. From the perspective of energy substitution, the expansion of renewable energy weakens dependence on fossil fuels, particularly coal, and promotes a transition toward a cleaner energy mix [18]. As renewable energy penetration increases, carbon-intensive energy sources may be gradually replaced by cleaner alternatives, which are associated with a lower carbon content of total energy consumption. In this context, ES, defined as the composition of energy use, particularly the relative share of fossil fuels versus low-carbon sources, plays a crucial role in determining carbon emission outcomes. Existing studies suggest that a higher share of low-carbon energy is associated with lower carbon intensity [30]. Therefore, REG is expected to be associated with lower CEI through a cleaner ES, which operates through structural substitution, i.e., changing “what type of energy is used”.

Hypothesis 3 (H3). *The REG–CEI association may partly operate through energy structure optimization.*

2.4. Mediating Role of Energy Intensity

Another possible mechanism underlying the REG-CEI association is EI. While the ES channel operates through changes in the composition of energy use, the EI channel reflects changes in the amount of energy required to support economic production. Renewable energy development is often accompanied by technological progress and may be linked to lower energy input requirements for economic output. As cleaner electricity replaces traditional energy sources and production processes become less energy-intensive, the amount of energy required per unit of output may be lower, which is generally associated with lower carbon-emission pressure even if the structure of electricity generation remains unchanged. In this sense, lower EI reflects a process in which economic output becomes less dependent on energy input. Existing studies indicate that reduction in EI is associated with lower CEI, while renewable energy development may be linked to this process through technological innovation and lower energy input requirements [39]. Therefore, this channel may help explain the association between REG and lower CEI by linking renewable electricity development to lower energy requirements per unit of output. Accordingly, REG is expected to be associated with lower CEI through reductions in EI.

Hypothesis 4 (H4). *The REG-CEI association may partly operate through lower energy intensity.*

3. Data and Methodology

This section describes the data, variable construction, and empirical strategy used in this study. The analysis proceeds in four steps. First, the main variables are defined and the provincial panel dataset is constructed. Second, the Tapio decoupling model is used to examine the dynamic evolution of the relationship between REG and CEI. Third, Moran's I statistics and the spatial Durbin model (SDM) are employed to test spatial dependence and estimate both local and spillover associations. Finally, robustness checks, endogeneity tests, heterogeneity analyses, and mechanism-related tests are conducted to evaluate the stability and potential channels of the baseline findings. A fixed-effects ordinary least squares (OLS) benchmark model is also estimated in Appendix C. To maintain a clear methodological narrative, more detailed operational procedures and supplementary specifications are reported in the Appendices A–D. All empirical analyses and figure generation were conducted using Stata 18.0 (StataCorp LLC, College Station, TX, USA).

3.1. Variable Definitions and Construction

3.1.1. Explained Variable: CEI

CEI is selected as the explained variable. Considering the potential measurement differences in carbon accounting, this study employs three alternative indicators of CEI derived from the Emissions Database for Global Atmospheric Research (EDGAR) and Carbon Emission Accounts and Datasets (CEADs) database [3]. Given its updated coverage, EDGAR is adopted as the primary data source, as it provides consistent carbon emission estimates up to 2024 and thus supports a more recent and comprehensive analysis.

The EDGAR database estimates carbon emissions under the IPCC framework, in which emissions are calculated by combining activity data and emission factors across sectors and energy types. Specifically, carbon emissions are derived from energy consumption, industrial processes, and other emission sources using internationally standardized parameters such as calorific values, carbon content, and oxidation rates. Based on this approach, the EDGAR-based carbon emission measure is used to construct *CEI_EDGAR* as the baseline proxy for CEI.

By contrast, the CEADs database is only available for earlier years. Accordingly, CEADs-based measures are used as robustness checks. Two alternative carbon emission

measures are constructed from CEADs. One is based on the sectoral accounting approach (IPCC method), while the other is based on the apparent energy consumption approach.

Based on these two carbon emission measures, CEI is further defined as CO₂ emissions per unit of provincial gross domestic product, as presented in Equation (1). Accordingly, CEI_EDGAR_{it} , CEI_IPCC_{it} and $CEI_apparent_{it}$ are used as three alternative dependent variables throughout the empirical analysis.

$$CEI^m_{it} = \frac{CO^m_{2it}}{provincial\ GDP_{it}}, i = 1, 2, \dots, 30, m \in \{EDGAR, IPCC, apparent\} \quad (1)$$

where CEI^m_{it} denotes CEI in province i and year t under accounting approach m , CO^m_{2it} denotes carbon emissions measured using approach m , and $provincial\ GDP_{it}$ denotes provincial gross domestic product. Accordingly, CEI_EDGAR_{it} , CEI_IPCC_{it} and $CEI_apparent_{it}$ are employed as three alternative dependent variables throughout the empirical analysis. Detailed formulas for the sectoral accounting and apparent energy consumption approaches are provided in Appendix A.

3.1.2. Core Explanatory Variable: REG

REG is the core explanatory variable. Renewable energy refers to non-fossil energy sources such as hydropower, wind, solar, biomass, and geothermal energy [11]. As a clean and low-carbon energy source, it is primarily used for power generation and plays an important role in ES improvement, carbon-emission mitigation, ecological protection, and climate-change responses. Following the existing literature, this study uses REG as the key proxy. Specifically, total REG is measured as the sum of hydropower generation, wind power generation, and solar power generation, as shown in Equation (2) [3,17,18].

To capture the relative importance of renewable energy in the provincial electricity mix, this study further constructs REG_share defined as the ratio of total REG to total electricity generation, as shown in Equation (3). This indicator reflects the penetration of renewable energy in the power structure and serves as an alternative explanatory variable in the baseline regression.

In addition, to capture the scale effect of renewable energy development, the logarithmic form of total REG, $lnREG$, is constructed according to Equation (4). This indicator reflects the scale of REG and is used as an alternative explanatory variable in the robustness checks.

By considering both the logarithmic scale measure and the share-based measure, this study captures renewable energy development from both absolute and relative perspectives, thereby providing a more comprehensive evaluation of its relationship with CEI.

$$ttlREG_{it} = hydropower\ generation_{it} + wind\ power\ generation_{it} + solar\ power\ generation_{it} \quad (2)$$

$$REG_share_{it} = \frac{ttlREG_{it}}{total\ electricity\ generation_{it}} \quad (3)$$

$$lnREG_{it} = \ln(ttlREG_{it}) \quad (4)$$

where $ttlREG_{it}$ denotes total REG; REG_share_{it} denotes the share of REG in total electricity generation; and $lnREG_{it}$ denotes the natural logarithm of total REG.

3.1.3. Control Variables

Several key control variables are included as follows: Economic development is measured by the logarithm of per capita GDP ($lnPGDP$), capturing the level of economic activity and scale effects [40–42]. Urbanization level ($Urban$) is included to reflect popu-

lation concentration and changes in consumption patterns associated with urban development [43–45]. Industrial structure (*Indst*) is measured by the ratio of added value of tertiary industry to that of secondary industry, reflecting structural upgrading and the relative importance of less energy-intensive sectors [43,46,47]. In addition, ER (*EnvirReg*) is incorporated to capture government efforts in pollution control and environmental protection [35,36,48,49].

3.2. Data Source

This study examines the evolution of the decoupling relationship, spatial spillover associations, and characteristic trends between REG and CEI in China over the period 2005 to 2024. Data on CEI are obtained from EDGAR and CEADs, including indicators calculated based on both the apparent energy consumption method and the sectoral accounting approach. Due to data availability constraints, the provincial wind and solar power generation data for 2024 are estimated using linear interpolation. All other data on REG are sourced from the China Energy Statistical Yearbook and the China Electric Power Statistical Yearbook. Control variables are collected from the China Statistical Yearbook and the National Bureau of Statistics. Due to data limitations, Tibet, Hong Kong, Taiwan, and Macau are excluded from the analysis. The final sample consists of 30 provinces and 600 province-year observations over the 20-year period. To mitigate the influence of outliers, all continuous variables are winsorized at the 1% level at both tails. To address this data limitation, a robustness check excluding 2024 observations is conducted in Section 4.2.2.

3.3. Model Specification

3.3.1. Tapio Model Specification

To preliminarily examine the relationship between REG and CEI, this study adopts the Tapio decoupling model, as shown in Equation (5). The Tapio model provides a flexible framework to assess the relative change between environmental pressure and economic or energy-related drivers and has been widely used in studies on energy-environment dynamics [50]. Compared with simple correlation or regression analysis, the Tapio decoupling elasticity captures the dynamic interaction between variables in a relative-growth framework, allowing for the identification of different decoupling states (e.g., strong decoupling, weak decoupling, or negative decoupling). It is therefore well suited to examining the evolution of the relationship between REG and CEI over time.

$$\varepsilon_{it} = \frac{\Delta \ln(CEI_{it})}{\Delta \ln(REG_{it})} = \frac{\ln(CEI_{it}) - \ln(CEI_{i,t-1})}{\ln(ttlREG_{it}) - \ln(ttlREG_{i,t-1})} \quad (5)$$

where ε_{it} represents the Tapio decoupling elasticity between REG and CEI. CEI_{it} denotes CEI_EDGAR_{it} , CEI_IPCC_{it} and $CEI_apparent_{it}$, respectively.

3.3.2. Spatial Weight Matrix and Moran's Index Setting

Given the strong regional interconnections in energy consumption, industrial structure, and environmental policies across provinces in China, CEI is likely to exhibit spatial dependence. Ignoring such spatial interactions may lead to biased estimation results. Therefore, this study first constructs spatial weight matrices and employs Moran's I statistic to test for spatial autocorrelation [4,5,24]. The spatial weight matrix defines the structure of spatial interactions across provinces, with the baseline specification based on geographical contiguity. Moran's I is then used to evaluate whether provinces with similar levels of CEI tend to cluster in space. A significantly positive Moran's I indicates spatial clustering, suggesting that regional CEI is shaped not only by local conditions but also by neighboring

provinces. This study employs three spatial weight matrices and constructs the following Moran's I model:

$$W_neighbor_{ij}^1 = \begin{cases} 1, & \text{if } i \text{ and } j \text{ are adjacent} \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

where $W_neighbor_{ij}^1 = 1$ if provinces i and j are geographically adjacent, and 0 otherwise.

$$W_distance_{ij}^2 = \begin{cases} 1/d_{ij}, & \text{if } i \neq j \\ 0, & \text{if } i = j \end{cases} \quad (7)$$

where $W_distance_{ij}^2 = \frac{1}{d_{ij}}$ for $i \neq j$, and d_{ij} denotes the geographical distance between provinces.

$$W_PGDP_{ij}^3 = \begin{cases} \frac{1}{|\overline{PGDP}_i - \overline{PGDP}_j|}, & \text{if } i \neq j \\ 0, & \text{if } i = j \end{cases} \quad (8)$$

where $W_PGDP_{ij}^3 = \frac{1}{|\overline{PGDP}_i - \overline{PGDP}_j|}$ for $i \neq j$, and $|\overline{PGDP}_i - \overline{PGDP}_j|$ denotes the difference in average per capita GDP between provinces.

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (9)$$

where I denotes the global Moran's I statistic used to test spatial autocorrelation of CEI. w_{ij} represents $W_neighbor_{ij}^1$, $W_distance_{ij}^2$, and $W_PGDP_{ij}^3$, respectively.

3.3.3. SDM Specification

Since the OLS framework assumes cross-sectional independence across provinces and does not account for potential spatial spillover effects, the OLS results offer useful preliminary evidence but may be incomplete if spatial dependence is present. To account for potential spatial dependence and spillover effects, this study employs the SDM [3,17,24]. Compared with traditional spatial econometric models such as the spatial lag model (SLM) and the spatial error model (SEM), the SDM incorporates both the spatial lag of the dependent variable and the spatial lags of explanatory variables, allowing for a more comprehensive characterization of spatial interactions. The SDM is particularly suitable in this context because renewable energy development, industrial structure, and environmental policies may generate cross-regional associations through channels such as technology diffusion, policy imitation, and inter-provincial energy markets. By including spatially lagged explanatory variables, the SDM enables the identification of both local and spillover associations of REG on CEI. The model is specified as follows:

$$CEI_{it} = \rho \sum_{j \neq i}^{30} w_{ij} CEI_{jt} + \beta REG_{it} + \theta \sum_{j \neq i}^{30} w_{ij} REG_{jt} + \delta Controls_{it} + \eta \sum_{j \neq i}^{30} w_{ij} Controls_{jt} + \mu_i + \gamma_t + \varepsilon_{it} \quad (10)$$

where W denotes the spatial weight matrix, and w_{ij} represents the spatial interaction between province i and province j . The parameter ρ captures the spatial dependence of the dependent variable, indicating the extent to which CEI in one province is associated with that in neighboring regions. The coefficients θ and η measure the spatial spillover associations of REG and control variables, respectively, reflecting how changes in explanatory variables in surrounding provinces are related to local CEI. Consistent with the baseline specification, $Controls_{it}$ includes economic development ($\ln PGDP$), urbanization level ($Urban$), industrial structure ($Indst$), and environmental regulation ($EnvirReg$). Furthermore, μ_i and γ_t denote province and year fixed effects, respectively, controlling

for unobserved heterogeneity across regions and over time, and ε_{it} is the idiosyncratic error term.

Since the decoupling analysis shows that the relationship between REG and CEI evolves over time, this study further adds the squared term of *REG_share* to test potential nonlinear effects, such as diminishing marginal returns or threshold effects.

$$CEI_{it} = \rho \sum_{j \neq i}^{30} w_{ij} CEI_{jt} + \beta_1 REG_{it} + \beta_2 REG_{it}^2 + \theta_1 \sum_{j \neq i}^{30} w_{ij} REG_{jt} + \theta_2 \sum_{j \neq i}^{30} w_{ij} REG_{jt}^2 + \delta Controls_{it} + \eta \sum_{j \neq i}^{30} w_{ij} Controls_{jt} + \mu_i + \gamma_t + \varepsilon_{it} \quad (11)$$

where REG_{it}^2 refers to the square term of REG, proxied by $REG_share_{it}^2$.

Table 1 provides detailed definitions and descriptions of all variables used in this study.

Table 1. Variable definitions and measurement (provincial level).

Name	Symbol	Variable Definitions
X: Core explanatory variables		
Renewable electricity generation	<i>REG_share</i>	Ratio of electricity generation from renewable energy source to total electricity generation in a given province-year, including hydropower, wind power and solar power, i.e., $\frac{(\text{hydropower} + \text{wind power} + \text{solar power generation})}{\text{total electricity generation}}$.
	<i>lnREG</i>	Natural log of the renewable electricity generation in a given province-year, including hydropower, wind power and solar power, i.e., $\ln(\text{hydropower generation} + \text{wind power generation} + \text{solar power generation})$.
Y: Explained variables		
Carbon emission intensity	<i>CEI_EDGAR</i>	Ratio of carbon emission quantity obtained from Emissions Database for Global Atmospheric Research (EDGAR) divided by provincial gross domestic product (GDP) in a given province-year, i.e., $\frac{\text{carbon emission amount acquired from EDGAR}}{\text{provincial GDP}}$.
	<i>CEI_IPCC</i>	Ratio of carbon emission quantity calculated by sectoral accounting approach (IPCC) divided by provincial gross domestic product (GDP) in a given province-year, i.e., $\frac{\text{carbon emission amount calculated by sectoral accounting}}{\text{provincial GDP}}$.
	<i>CEI_apparent</i>	Ratio of carbon emission quantity calculated by apparent accounting approach divided by provincial gross domestic product (GDP) in a given province-year, i.e., $\frac{\text{carbon emission amount calculated by apparent accounting}}{\text{provincial GDP}}$.
Control variables		
Economic growth	<i>lnPGDP</i>	Natural log of per capita GDP (yuan/human), i.e., $\ln(\text{PGDP})$.
Urbanization	<i>Urban</i>	The urbanization level in China: ratio of provincial urban population to total population (%), i.e., $\frac{\text{provincial urban population}}{\text{total population}}$.
Industrial structure upgrading and optimization	<i>Indst</i>	Ratio of added value of tertiary industry to that of secondary industry (%), i.e., $\frac{\text{tertiary industry added value}}{\text{secondary industry added value}}$.
Environment	<i>EnvirReg</i>	Environmental regulation: ratio of completed investment in industrial pollution control to the added value of secondary industry (%), i.e., $\frac{\text{the completed investment in industrial pollution control}}{\text{secondary industry added value}}$.

Table 1. Cont.

Name	Symbol	Variable Definitions
Foreign direct investment	<i>FDI</i>	Ratio of actual utilization FDI to the GDP of each province (%), i.e., $\frac{\text{actual utilization FDI}}{\text{provincial GDP}}$.
Technological innovation	<i>Tech</i>	Ratio of R&D expenditure to GDP (%), i.e., $\frac{\text{provincial R\&D expenditure}}{\text{provincial GDP}}$.
Forest coverage	<i>Forest</i>	Ratio of forest coverage.
Mediating variables		
Energy structure	<i>ES</i>	Ratio of coal consumption to primary energy consumption (%), i.e., $\frac{\text{coal consumption} \times 0.714}{\text{provincial primary energy consumption}}$.
Energy intensity	<i>EI</i>	Ratio of primary energy consumption (ton/10,000 yuan) to provincial GDP, i.e., $\frac{\text{provincial primary energy consumption}}{\text{provincial GDP}}$.

4. Empirical Analysis

4.1. Descriptive Trend Analysis

Table 2 reports the descriptive statistics of the main variables. REG exhibits substantial variation across provinces. In particular, the mean of *REG_share* is 0.234, with a standard deviation of 0.237, while *lnREG* also shows wide dispersion, indicating clear regional differences in the scale and structure of REG. For the dependent variables, the mean values of *CEI_EDGAR*, *CEI_IPCC* and *CEI_apparent* are 2.118, 2.212, and 2.515, respectively, suggesting that the apparent accounting approach generally yields a higher level of CEI than the sectoral accounting approach. Among the control variables, *lnPGDP*, *Urban*, *Indst* and *Forest* show relatively stable distributions, whereas *FDI* and *Tech* have fewer observations because of data availability constraints. The descriptive statistics indicate considerable cross-provincial heterogeneity and provide a suitable basis for the subsequent empirical analysis.

Table 2. Descriptive summary statistics.

Var Name	Obs.	Mean	SD	Min	Median	Max
<i>REG_share</i>	600	0.234	0.237	0.000	0.147	0.891
<i>lnREG</i>	600	5.002	1.996	−1.802	5.534	8.189
<i>CEI_EDGAR</i>	600	2.118	1.510	0.214	1.656	7.638
<i>CEI_IPCC</i>	510	2.212	1.490	0.316	1.838	7.137
<i>CEI_apparent</i>	540	2.515	2.250	0.224	1.807	11.785
<i>lnPGDP</i>	600	10.641	0.692	9.034	10.715	12.202
<i>Urban</i>	600	0.574	0.139	0.300	0.568	0.893
<i>Indst</i>	600	1.332	0.746	0.578	1.172	5.289
<i>EnvirReg</i>	600	0.003	0.003	0.0001	0.002	0.014
<i>FDI</i>	559	0.021	0.020	0.0004	0.017	0.103
<i>Tech</i>	480	0.011	0.006	0.002	0.009	0.028
<i>Forest</i>	600	0.337	0.180	0.042	0.373	0.668

Table 3 presents the pairwise correlation coefficients among the main variables used in the baseline analysis. *REG_share* is negatively correlated with urbanization, ER, and, to a lesser extent, industrial structure, suggesting that provinces with higher levels of urbanization and stricter ER tend to have a lower share of renewable energy in total electricity generation. This pattern reflects structural differences in energy consumption across regions. Similarly, *lnREG* also shows negative correlations with these variables, indicating that both the scale and the share of renewable energy are systematically associated with

regional economic and structural characteristics. These findings imply that the spatial distribution of renewable energy is not random but closely linked to underlying economic development and policy conditions.

Table 3. Correlation coefficient.

Variables	<i>REG_share</i>	<i>lnREG</i>	<i>lnPGDP</i>	<i>Urban</i>	<i>Indst</i>	<i>EnvirReg</i>
<i>REG_share</i>	1					
<i>lnREG</i>	0.674 ***	1				
<i>lnPGDP</i>	−0.141 ***	0.102 **	1			
<i>Urban</i>	−0.340 ***	−0.243 ***	0.858 ***	1		
<i>Indst</i>	−0.067	−0.149 ***	0.492 ***	0.550 ***	1	
<i>EnvirReg</i>	−0.099 **	−0.215 ***	−0.502 ***	−0.359 ***	−0.247 ***	1

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

4.1.1.1. Decoupling Relationship Evolution

Figure 3 (including Figure A2 in Appendix B) illustrates the evolution of the decoupling relationship between REG and CEI. The results show that the relationship has gradually shifted from an unstable and weak decoupling state to a more stable strong decoupling state over the sample period. In the early stage before around 2008, the decoupling elasticity fluctuates around zero and occasionally enters expansive or weak decoupling states, suggesting that the expansion of REG was not yet consistently associated with lower CEI. This may reflect the relatively limited scale of renewable electricity deployment and the continued dominance of fossil-fuel-based energy consumption during the early transition period. During the intermediate stage from approximately 2008 to 2014, the elasticity becomes more stable and gradually moves toward weak decoupling, indicating that renewable electricity development became more consistently linked to improvements in carbon efficiency. This transition coincides with the acceleration of clean energy policies, technological progress, and the gradual expansion of renewable electricity capacity. After around 2014, the decoupling relationship further strengthens into strong decoupling, with REG continuing to increase while CEI declines. This pattern suggests that renewable electricity development is not only expanding in scale, but is also increasingly associated with structural improvements in the energy system and carbon efficiency. Overall, Figure 3 suggests that the role of renewable electricity in China's low-carbon transition has evolved from an initially unstable association to a more stable association with carbon-intensity decoupling.

Figure 4 (including Figures A3 and A4 in Appendix B) illustrates the spatial distribution of CEI across provinces in selected years under different accounting approaches. Rather than showing a random distribution, the maps reveal a persistent spatial pattern characterized by relatively high CEI in northern and northwestern China and relatively low CEI in coastal and southern provinces. In 2005, high-CEI provinces were mainly concentrated in Inner Mongolia, Shanxi, Ningxia, Xinjiang, and parts of Hebei, which are generally characterized by coal-abundant resource endowments, heavy industrial structures, and higher dependence on fossil energy. By contrast, lower CEI values were mainly observed in coastal and southern provinces such as Guangdong, Fujian, Jiangxi, and Hainan, where industrial structures are relatively less energy-intensive and the service sector accounts for a larger share of economic activity. Over time, the overall level of CEI declines, particularly in eastern and central provinces, indicating improvements in carbon efficiency. However, the relative spatial ranking of provinces remains highly stable. The core high-CEI regions in northern and northwestern China continue to exhibit relatively high carbon intensity even in the later period, while many coastal and southern provinces remain in lower-intensity groups. This pattern suggests that the decline in CEI is not sufficient to eliminate the

underlying spatial imbalance. Instead, carbon intensity appears to be shaped by persistent structural factors, including coal dependence, industrial composition, energy infrastructure, and regional development patterns.

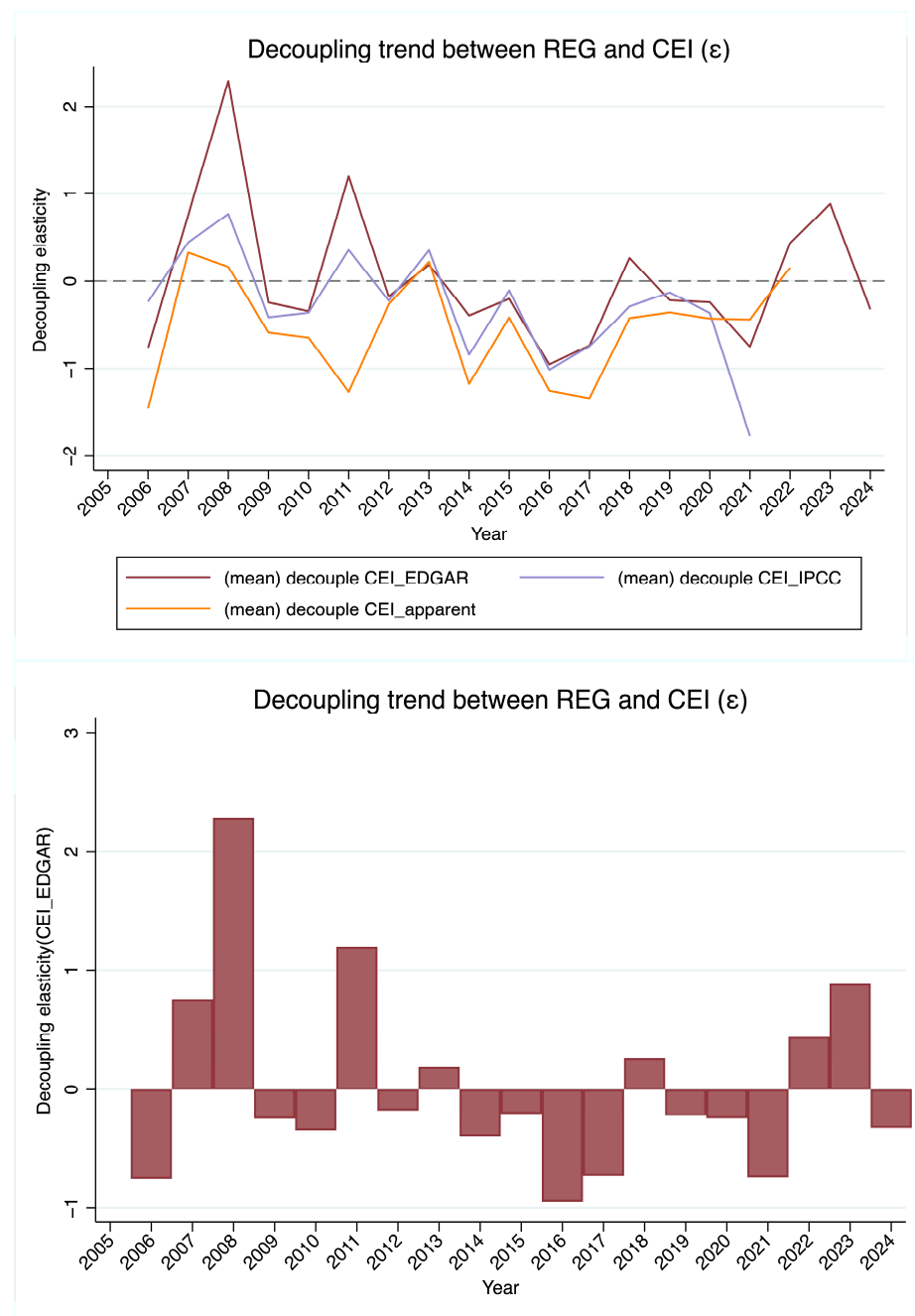


Figure 3. Decoupling trend between REG and CEI, 2005–2024. Note: The dashed horizontal line indicates the zero-decoupling threshold.

The maps therefore provide useful descriptive evidence that CEI in China is path-dependent and regionally clustered, which supports the use of spatial econometric models in the subsequent analysis. The stable concentration of high-CEI provinces and the similarity of spatial patterns across EDGAR, sectoral, and apparent accounting approaches indicate that local carbon outcomes may be linked to neighboring provinces through energy supply chains, industrial linkages, and regional policy interactions. This provides visual evidence that distinguishing local associations from spatial spillover associations is important in the regression analysis.

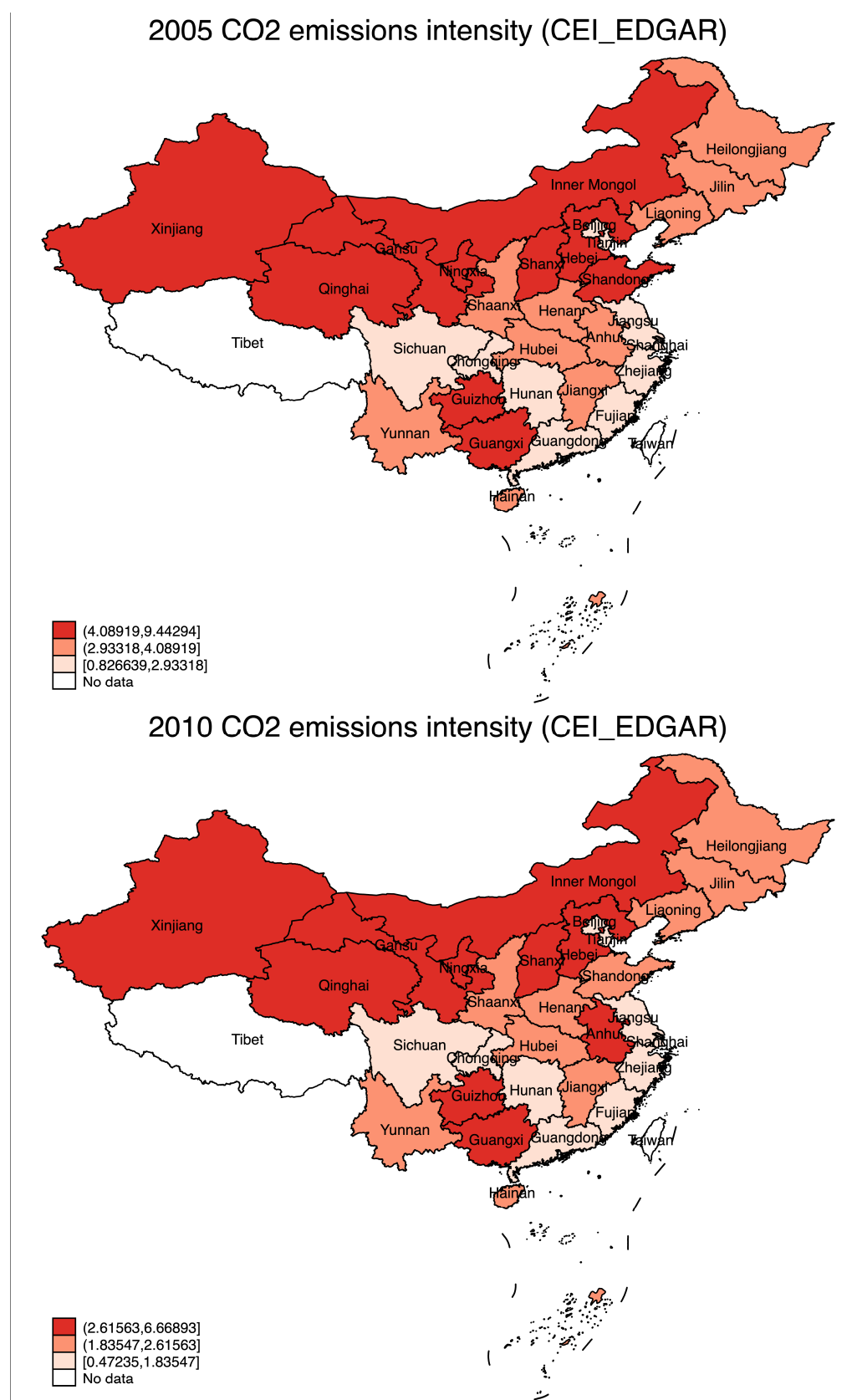


Figure 4. Cont.

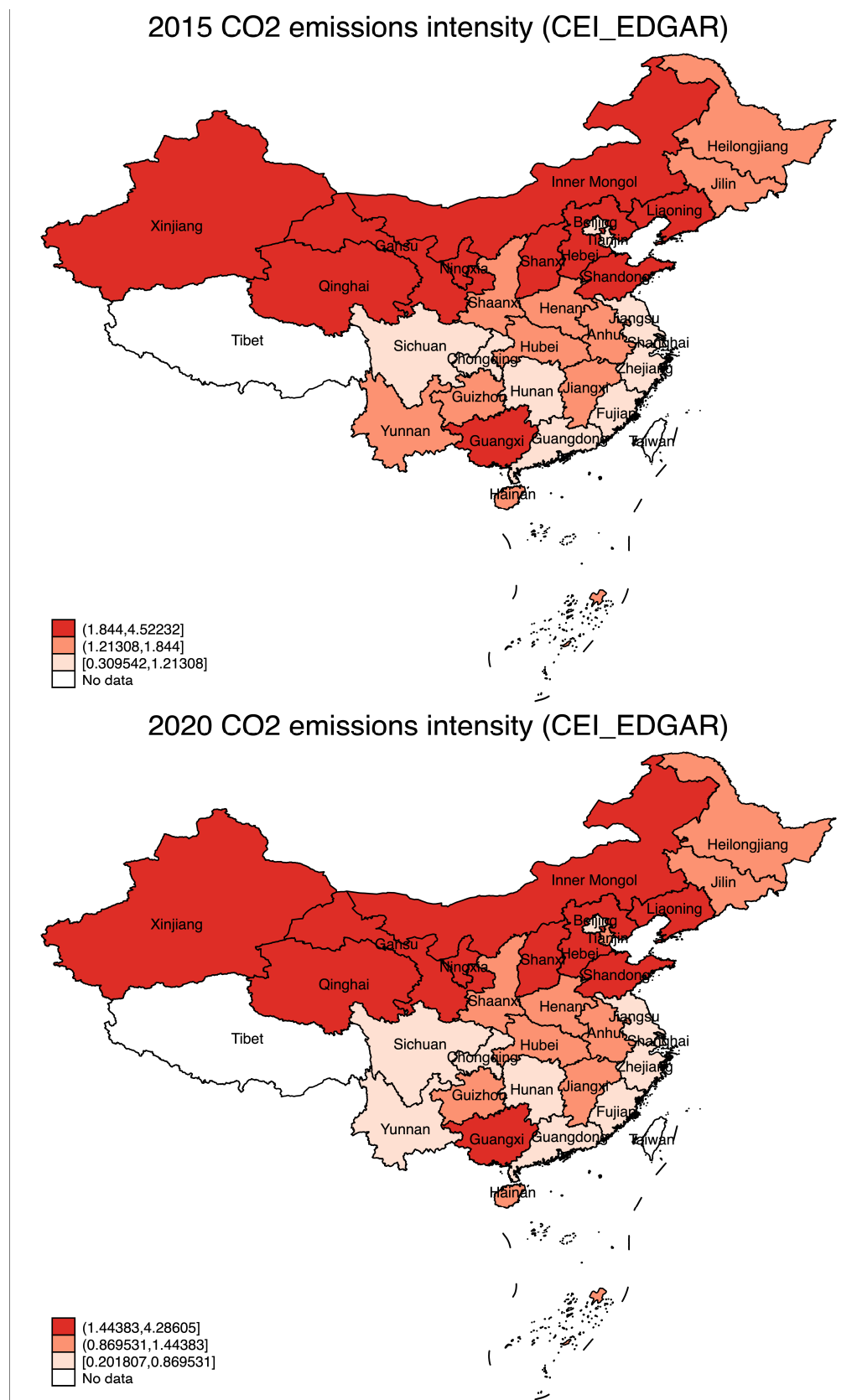


Figure 4. Cont.

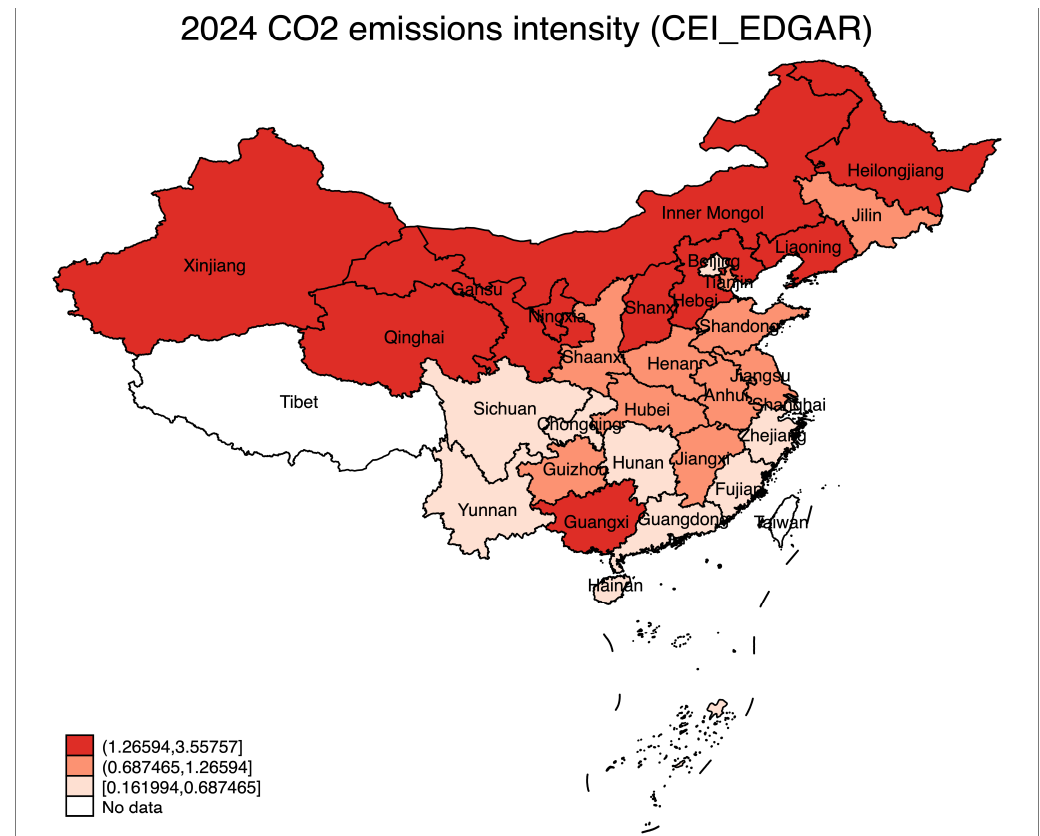


Figure 4. Spatial distribution of *CEI_EDGAR* across 30 provinces in selected years (2005, 2010, 2015, 2020, 2024).

4.1.2. Moran's Index Analysis

Table 4 reports the global Moran's I statistics of CEI under three accounting approaches and two spatial weight matrices. The results show that all reported Moran's I values are positive and statistically significant at the 1% level throughout the sample period, indicating a stable and significant positive spatial autocorrelation in provincial CEI. Specifically, under the contiguity matrix $W_{neighbor}^1$, the Moran's I values of *CEI_EDGAR* range from 0.294 to 0.489 during 2005 to 2024, while those of *CEI_IPCC* range from 0.327 to 0.442 (2005 to 2021), and those of *CEI_apparent* range from 0.265 to 0.431 (2005 to 2022). These results suggest that the spatial clustering pattern is consistently strong across different accounting methods, with EDGAR-based estimates exhibiting slightly higher spatial dependence in recent years. Under the distance matrix $W_{distance}^2$, the corresponding Moran's I values are smaller, ranging from approximately 0.106 to 0.123 for *CEI_EDGAR*, from 0.070 to 0.108 for *CEI_IPCC*, and from 0.053 to 0.097 for *CEI_apparent*, but they remain significantly positive in all reported years. This indicates that although spatial dependence weakens with increasing geographic distance, it remains statistically significant. These findings indicate that CEI in China is not randomly distributed across provinces. Instead, provinces with relatively high CEI tend to be located near provinces with similarly high levels, while low-emission-intensity provinces are more likely to cluster with each other. Moreover, the spatial dependence captured by the contiguity matrix is consistently stronger than that captured by the distance matrix, implying that direct geographic adjacency plays a more important role than pure geographic distance in shaping the spatial pattern of CEI.

Table 4. Moran’s Index using two weight matrices.

Year	CEI_EDGAR	CEI_IPCC	CEI_apparent	Year	CEI_EDGAR	CEI_IPCC	CEI_apparent
Panel A: $W_{neighbor}^1_{ij}$							
2005	0.327 *** (2.945)	0.343 *** (3.091)	0.431 *** (3.976)	2015	0.433 *** (3.827)	0.442 *** (4.011)	0.270 *** (2.949)
2006	0.294 *** (2.686)	0.327 *** (2.967)	0.354 *** (3.411)	2016	0.433 *** (3.831)	0.433 *** (3.886)	0.265 *** (2.952)
2007	0.310 *** (2.840)	0.348 *** (3.170)	0.367 *** (3.780)	2017	0.455 *** (4.024)	0.408 *** (3.791)	0.285 *** (3.017)
2008	0.339 *** (3.063)	0.396 *** (3.607)	0.380 *** (3.534)	2018	0.456 *** (4.050)	0.408 *** (3.802)	0.282 *** (3.009)
2009	0.341 *** (3.074)	0.392 *** (3.540)	0.329 *** (3.181)	2019	0.445 *** (4.010)	0.401 *** (3.778)	0.295 *** (3.073)
2010	0.366 *** (3.330)	0.441 *** (3.969)	0.390 *** (3.635)	2020	0.460 *** (4.121)	0.411 *** (3.881)	0.286 *** (3.040)
2011	0.381 *** (3.479)	0.398 *** (3.774)	0.406 *** (3.814)	2021	0.470 *** (4.225)	0.419 *** (3.963)	0.271 *** (2.856)
2012	0.381 *** (3.451)	0.424 *** (3.917)	0.413 *** (3.815)	2022	0.470 *** (4.223)	.	0.266 *** (2.831)
2013	0.385 *** (3.467)	0.401 *** (3.701)	0.300 *** (3.080)	2023	0.480 *** (4.312)	.	.
2014	0.396 *** (3.540)	0.427 *** (3.904)	0.286 *** (3.013)	2024	0.489 *** (4.364)	.	.
Panel B: $W_{distance}^2_{ij}$							
2005	0.113 *** (4.073)	0.077 *** (3.119)	0.097 *** (3.807)	2015	0.123 *** (4.390)	0.108 *** (4.089)	0.056 *** (2.962)
2006	0.106 *** (3.919)	0.070 *** (2.933)	0.076 *** (3.313)	2016	0.119 *** (4.274)	0.107 *** (4.012)	0.053 *** (2.920)
2007	0.113 *** (4.138)	0.074 *** (3.074)	0.070 *** (3.332)	2017	0.122 *** (4.388)	0.096 *** (3.800)	0.056 *** (2.899)
2008	0.115 *** (4.173)	0.089 *** (3.538)	0.084 *** (3.445)	2018	0.123 *** (4.422)	0.099 *** (3.886)	0.059 *** (3.034)
2009	0.119 *** (4.277)	0.089 *** (3.498)	0.077 *** (3.314)	2019	0.119 *** (4.374)	0.093 *** (3.762)	0.060 *** (3.003)
2010	0.118 *** (4.322)	0.096 *** (3.716)	0.085 *** (3.487)	2020	0.119 *** (4.354)	0.092 *** (3.758)	0.057 *** (2.936)
2011	0.118 *** (4.343)	0.083 *** (3.486)	0.088 *** (3.617)	2021	0.119 *** (4.361)	0.094 *** (3.824)	0.055 *** (2.852)
2012	0.118 *** (4.310)	0.096 *** (3.804)	0.093 *** (3.694)	2022	0.116 *** (4.282)	.	0.055 *** (2.862)
2013	0.118 *** (4.296)	0.098 *** (3.837)	0.070 *** (3.277)	2023	0.117 *** (4.307)	.	.
2014	0.118 *** (4.271)	0.105 *** (4.008)	0.064 *** (3.146)	2024	0.121 *** (4.403)	.	.

Notes: Z-statistics in parentheses. *** $p < 0.01$. A dot (.) indicates that the corresponding CEADs-based data are unavailable for that year. Panel A employs the spatial weight matrix of $W_{neighbor}^1_{ij}$. Panel B employs the spatial weight matrix of $W_{distance}^2_{ij}$.

Figure 5 presents the Moran scatterplots of CEI under different accounting approaches. The positive slope of the fitted line is consistent with significant positive spatial autocorrelation, in line with the global Moran’s I results. More importantly, the distribution of provinces across the four quadrants provides additional insight into the spatial structure of CEI. A large number of provinces fall into the high–high (HH) and low–low (LL) quadrants, indicating that provinces with high CEI tend to be surrounded by similarly high-

intensity provinces, while low-intensity provinces tend to cluster with other low-intensity provinces. The HH clustering pattern is mainly associated with resource-dependent and heavy-industrial provinces, such as Inner Mongolia, Shanxi, and Ningxia. These provinces are often embedded in fossil-energy production systems and energy-intensive industrial chains, which may reinforce similar carbon intensity patterns across neighboring regions. In contrast, the LL clustering pattern is more common in coastal and southern provinces, such as Guangdong, Fujian, and Hainan, where relatively cleaner industrial structures, higher energy efficiency, and stronger service-sector development may contribute to lower carbon intensity. The relatively small number of observations in the low-high (LH) and high-low (HL) quadrants suggests that spatial outliers exist but are not dominant, implying that CEI is mainly characterized by regional clustering rather than isolated provincial deviations.

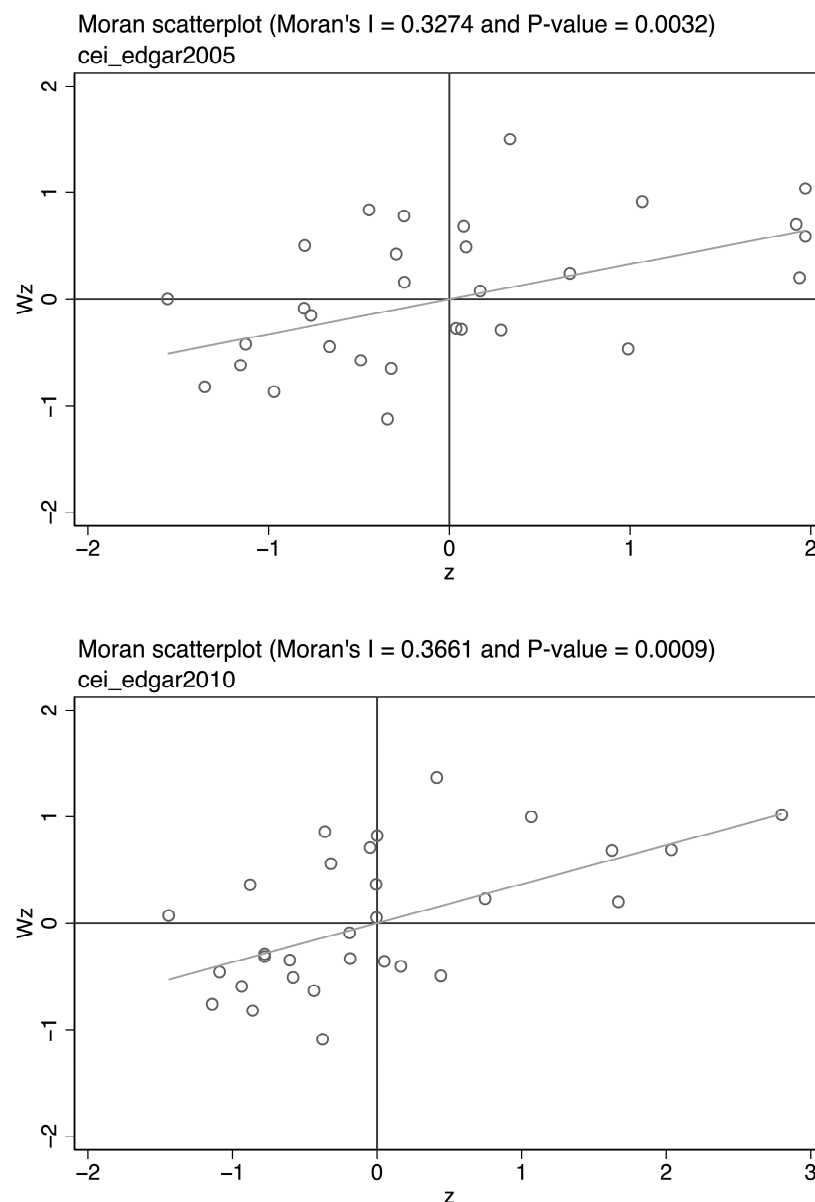


Figure 5. Cont.

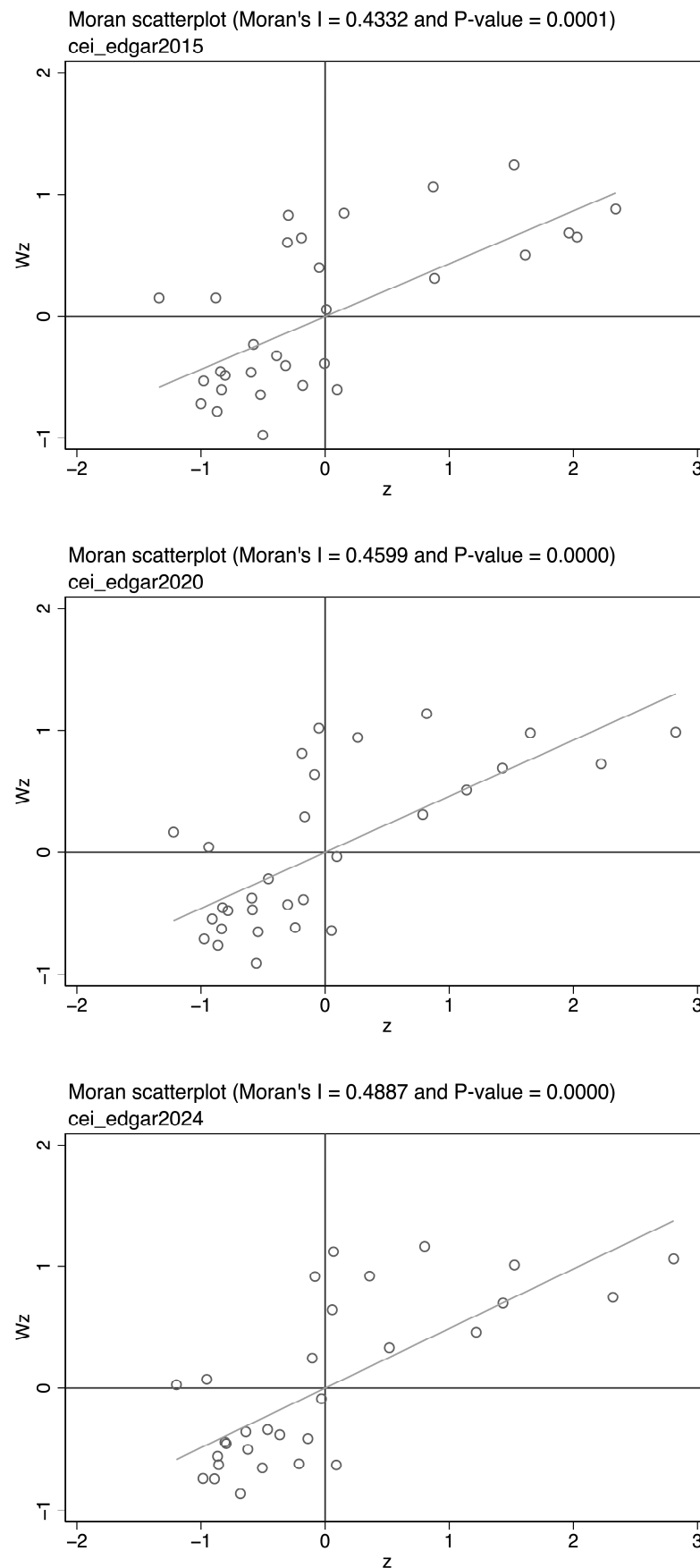


Figure 5. Moran's Index scatterplot of *CEI_EDGAR* using provincial neighbor matrix weight ($W_{neighbor_{ij}^1}$) in selected years (2005, 2010, 2015, 2020, 2024). Note: The diagonal fitted line indicates the spatial association between provincial CEI and its spatial lag.

From an economic perspective, such clustering may be driven by several structural factors. First, provinces often share similar energy resource endowments, such as coal abundance or renewable energy potential, which leads to comparable energy consumption patterns and carbon intensity levels. Second, neighboring regions tend to exhibit similar industrial structures due to geographic proximity and economic linkages, particularly the concentration of energy-intensive industries. Third, regional policy environments and environmental regulations may display spatial correlation, as local governments often learn from or imitate policy practices in adjacent regions. Finally, interregional economic interactions, including energy trade and technological diffusion, further reinforce the spatial dependence in CEI. Overall, these factors jointly contribute to the observed spatial clustering pattern. These findings further imply that changes in CEI in one region may be linked to developments in neighboring regions, suggesting the need to examine potential spatial spillover associations in the regression analysis.

4.2. Regression Analysis

4.2.1. Baseline Analysis

Tables 5, A1 and A2 in Appendix D report the results of spatial econometric model selection tests using three spatial weight matrices. The LM and robust LM tests for both SLM and SEM are highly significant, indicating the presence of spatial dependence in CEI. Furthermore, the LR and Wald tests both reject the null hypotheses that the SDM can be simplified into either the SLM or the SEM, suggesting that the SDM specification should be retained. In addition, the joint significance of both individual and time fixed effects suggests that the two-way fixed effects SDM specification is appropriate. Therefore, the two-way fixed effects SDM is selected as the baseline model.

Table 5. Test results of spatial econometric model selection using $W_neighbor_{ij}^1$.

Matrix: $W_neighbor_{ij}^1$ (Provincial Neighbor Weight Matrix)				
Panel A: REG_share and CEI_EDGAR				
	Spatial error		Spatial lag	
LM test	LM-error	61.323 ***	LM-lag	37.675 ***
	Robust-LM-error	29.986 ***	Robust-LM-lag	6.338 **
LR test	LR-error	53.050 ***	LR-lag	62.490 ***
Wald test	Wald-error	55.370 ***	Wald-lag	66.770 ***
Spatial Durbin's Model				
Fixed effect test	Both vs. Individual fixed	119.140 ***	Both vs. Time fixed	1148.250 ***
Panel B: $lnREG$ and CEI_EDGAR				
	Spatial error		Spatial lag	
LM test	LM-error	71.489 ***	LM-lag	45.063 ***
	Robust-LM-error	34.420 ***	Robust-LM-lag	7.993 ***
LR test	LR-error	46.840 ***	LR-lag	51.120 ***
Wald test	Wald-error	48.420 ***	Wald-lag	53.770 ***
Spatial Durbin's Model				
Fixed effect test	Both vs. Individual fixed	90.630 ***	Both vs. Time fixed	1121.660 ***

Notes: The reported values correspond to test statistics from LM, LR, Wald and fixed effect tests, which follow a chi-square distribution. *** $p < 0.01$, ** $p < 0.05$. REG_share and $lnREG$ denote renewable electricity generation (REG). CEI_EDGAR denotes carbon emission intensity (CEI). Panel A represents the results between REG_share and CEI_EDGAR . Panel B represents the results between $lnREG$ and CEI_EDGAR .

Table 6 presents the SDM estimation results using matrix $W_neighbor_{ij}^1$. In Panel A, Columns (1) to (3) report the association between REG_share and CEI_EDGAR , while

Columns (4) to (6) report the results for *lnREG* and *CEI_EDGAR*. In each group, the first column reports the coefficients of the main explanatory variables, the second column reports the spatial lag terms (Wx), and the third column presents the full specification including spatial dependence. Focusing on the main coefficients, REG is significantly associated with lower CEI in both Panel A specifications, suggesting a negative local association between REG and CEI. The magnitude of the coefficients remains relatively stable, suggesting a robust local association. Regarding the spatially lagged term (Wx), the coefficient of REG is also significantly negative, suggesting the presence of negative spatial interaction across regions. This result suggests that higher REG in one province is associated not only with lower local CEI but also with lower CEI in neighboring provinces.

The spatial autoregressive coefficient ρ is significantly negative across specifications. This result should be interpreted cautiously and does not necessarily contradict the positive spatial clustering indicated by Moran's I. Moran's I captures the unconditional spatial association of CEI, whereas ρ reflects conditional spatial dependence after controlling for REG, socioeconomic characteristics, and province and year fixed effects. Therefore, the positive Moran's I indicates that provinces with similar carbon-intensity levels tend to cluster spatially, while the negative ρ suggests that, after accounting for observed determinants and fixed effects, changes in CEI may involve a substitutive or redistributive relationship across neighboring provinces.

This interpretation is consistent with previous spatial environmental studies. For example, clean energy investment has been found to be associated with lower domestic carbon emissions while generating adverse spillover effects in neighboring economies, which has been interpreted as a carbon leakage effect [51]. Similarly, studies on China's energy-consuming right trading policy show that energy-efficiency improvements in pilot areas may be accompanied by industrial transfer and negative spatial spillovers to neighboring non-pilot areas [52]. Spatial econometric studies of China's carbon emissions also indicate that regional carbon outcomes are shaped by both local factors and spatial interactions, rather than by purely local processes [53]. In this context, the negative ρ may reflect cross-regional adjustment mechanisms, such as the relocation of energy-intensive industries, interprovincial electricity trade, and competition for energy-intensive investment. Thus, the results suggest that regional carbon mitigation is not always spatially reinforcing; instead, it may also involve redistribution and adjustment across provinces. This finding highlights the importance of coordinating renewable electricity development, industrial policy, and interprovincial energy allocation across regions.

To further interpret the spatial effects, Panel B reports the decomposition into direct, indirect, and total effects. Columns (1) to (3) report the direct effect, indirect effect and total effect of *REG_share* on *CEI_EDGAR*, while Columns (4) to (6) present the same effects of *lnREG* on *CEI_EDGAR*. The results show that the direct effect of REG is significantly negative, indicating that renewable electricity development is associated with lower CEI within the local province. Economically, this local association may be related to the substitution of fossil-fuel-based electricity, improvements in the provincial energy mix, and greater use of low-carbon electricity in industrial and residential consumption. The indirect effect is also significantly negative, suggesting that REG is associated with lower CEI beyond provincial boundaries. This spillover effect may reflect the interregional nature of China's electricity system. Renewable electricity generated in one province may be linked to neighboring provinces through interprovincial power transmission, electricity market linkages, energy supply-chain adjustment, and the diffusion of low-carbon technologies and policy practices. In this sense, renewable electricity development may be understood not only as a local environmental strategy, but also as part of a cross-regional mitigation framework. The significantly negative total effect further suggests that the overall association between REG

and lower CEI is larger than the local association alone, highlighting the importance of coordinated regional energy governance and grid integration.

Table 6. SDM baseline results using $W_{neighbor_{ij}}^1$.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Parameter results (CEI_EDGAR)						
	Main (β)	WX (θ)	Spatial	Main (β)	WX (θ)	Spatial
<i>REG_share</i>	−0.963 *** (0.293)	−2.375 *** (0.496)				
<i>lnREG</i>				−0.072 *** (0.022)	−0.111 *** (0.036)	
<i>lnPGDP</i>	−0.693 *** (0.190)	1.542 *** (0.356)		−0.870 *** (0.201)	1.146 *** (0.383)	
<i>Urban</i>	−5.993 *** (0.847)	−8.207 *** (1.646)		−5.723 *** (0.847)	−6.994 *** (1.677)	
<i>Indst</i>	0.400 *** (0.083)	0.219 (0.171)		0.437 *** (0.084)	0.479 *** (0.174)	
<i>EnvirReg</i>	4.127 (7.880)	−4.178 (15.750)		13.56 * (7.963)	45.31 *** (15.350)	
Rho (ρ)			−0.230 *** (0.058)			−0.166 *** (0.057)
R ²	0.338	0.338	0.338	0.406	0.406	0.406
Observations	600	600	600	600	600	600
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Direct, indirect and total effect (CEI_EDGAR)						
	Direct	Indirect	Total	Direct	Indirect	Total
<i>REG_share</i>	−0.843 *** (0.314)	−1.843 *** (0.449)	−2.686 *** (0.338)			
<i>lnREG</i>				−0.068 *** (0.024)	−0.087 *** (0.033)	−0.155 *** (0.027)
<i>lnPGDP</i>	−0.788 *** (0.186)	1.472 *** (0.313)	0.684 ** (0.305)	−0.926 *** (0.194)	1.164 *** (0.346)	0.238 (0.364)
<i>Urban</i>	−5.555 *** (0.831)	−5.950 *** (1.339)	−11.51 *** (1.309)	−5.406 *** (0.821)	−5.460 *** (1.419)	−10.87 *** (1.436)
<i>Indst</i>	0.395 *** (0.083)	0.120 (0.137)	0.515 *** (0.164)	0.425 *** (0.083)	0.371 *** (0.143)	0.796 *** (0.171)
<i>EnvirReg</i>	4.445 (7.816)	−3.726 (13.870)	0.719 (13.960)	11.990 (7.824)	38.760 *** (13.790)	50.740 *** (13.880)
R ²	0.338	0.338	0.338	0.406	0.406	0.406
Observations	600	600	600	600	600	600
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$. *REG_share* and *lnREG* denote REG. *CEI_EDGAR* denotes CEI. Panel A shows the analysis of SDM results. Panel B shows the decomposition of SDM effects, including direct, indirect and total effect.

Table A3 in Appendix D reports the OLS estimation results. Columns (1) to (3) show the associations of *REG_share* with *CEI_EDGAR*, *CEI_IPCC* and *CEI_apparent*, respectively. The coefficients of REG remain significantly negative, providing benchmark evidence consistent with the SDM results.

Overall, the baseline results provide evidence that REG is significantly associated with lower CEI, and that this association exhibits clear spatial spillover patterns across provinces.

4.2.2. Robustness Checks

(1) Summary of robustness checks

To examine whether the baseline findings are sensitive to data coverage, variable measurement, spatial dependence specification, regional policy heterogeneity, and model dynamics, this study conducts a series of robustness checks. First, since the 2024 wind and

solar power generation data are estimated by interpolation, the sample excluding 2024 is used to test whether the baseline findings are driven by interpolated observations. In addition, the 2005–2019 sample is used to match the period of the mechanism analysis and examine whether the results are sensitive to sample-period differences. Second, alternative CEI measures based on the sectoral accounting approach and the apparent energy consumption approach are employed to test measurement robustness. Third, region-by-year fixed effects are included to absorb time-varying regional policy shocks and regional development differences. Fourth, alternative spatial weight matrices are used to examine whether the results depend on the definition of spatial linkages. Fifth, a dynamic SDM is estimated to account for the persistence of CEI. Finally, additional control variables, including foreign direct investment (*FDI*), technological innovation (*Tech*), and forest coverage (*Forest*), are also gradually introduced into the OLS regression model.

Table 7a summarizes the main robustness results. Across the alternative sample periods, alternative CEI measures, region-by-year fixed effects, alternative spatial matrices, and dynamic SDM specifications, REG remains negatively associated with CEI in most specifications. More importantly, the direct, indirect, and total effects of REG are generally negative and statistically significant, indicating that the baseline conclusions are not driven by a specific sample period, carbon accounting method, spatial matrix, fixed-effect structure, or model specification. These results provide consistent support for the robustness of the local and spatial mitigation associations identified in the baseline SDM. To maintain readability, Table 7a reports only the core coefficients and SDM effect decompositions, while the full estimation results are reported in Appendix D, Tables A4–A11. Table A12 in Appendix D reports the results of adding more control variables using OLS. Although the inclusion of these variables leads to a reduction in sample size due to missing observations, the coefficient of REG remains significantly negative. This helps alleviate concerns that the baseline association is driven by omitted variables and suggests that the results are robust to the inclusion of additional controls.

Table 7. (a) Summary of robustness checks. (b) Nonlinear SDM test with the square term of $REG (W_{neighbor}^1_{ij})$.

(a)							
Robustness Checks	Main (β)	WX (θ)	Rho (ρ)	Direct	Indirect	Total	Full Results
<i>REG_share</i> and <i>CEI_EDGAR</i> using $W_{neighbor}^1_{ij}$							
Excluding 2024 (2005–2023)	−0.951 ***	−2.551 ***	−0.223 ***	−0.824 **	−2.009 ***	−2.833 ***	Table A4
Unified sample period (2005–2019)	−1.870 ***	−1.772 ***	−0.069	−1.831 ***	−1.541 **	−3.371 ***	Table A5
Alternative Y: <i>CEI_IPCC</i>	−2.032 ***	−1.440 **	−0.076	−1.998 ***	−1.194 **	−3.192 ***	Table A6
Alternative Y: <i>CEI_apparent</i>	−2.681 ***	−2.072 *	−0.065	−2.630 ***	−1.769 *	−4.399 ***	Table A7
Region × Year FE	−1.218 ***	−2.364 ***	−0.510 ***	−1.014 ***	−1.350 ***	−2.364 ***	Table A8
Alternative matrix: $W_{distance}^2_{ij}$	−0.892 ***	−3.822 **	0.209	−0.937 ***	−5.021 **	−5.958 ***	Table A9
Alternative matrix: $W_{PGDP}^3_{ij}$	−1.645 ***	−1.893 ***	−0.066	−1.614 ***	−1.673 ***	−3.287 ***	Table A10
Dynamic SDM: <i>L.CEI_EDGAR</i>	−0.257 **	−0.055	0.029	−0.262 **	−0.0638	−0.325 *	Table A11
<i>lnREG</i> and <i>CEI_EDGAR</i> using $W_{neighbor}^1_{ij}$							
Excluding 2024 (2005–2023)	−0.068 ***	−0.113 ***	−0.155 ***	−0.064 ***	−0.091 ***	−0.154 ***	Table A4
Unified sample period (2005–2019)	−0.017	−0.143 ***	0.055	−0.017	−0.149 ***	−0.166 ***	Table A5
Alternative Y: <i>CEI_IPCC</i>	−0.0133	−0.131 ***	0.047	−0.014	−0.135 ***	−0.149 ***	Table A6
Alternative Y: <i>CEI_apparent</i>	−0.078 *	−0.151 **	0.010	−0.077	−0.150 **	−0.227 ***	Table A7
Region × Year FE	−0.080 ***	−0.122 ***	−0.532 ***	−0.069 ***	−0.0628 **	−0.132 ***	Table A8
Alternative matrix: $W_{distance}^2_{ij}$	−0.093 ***	−0.154	0.245 *	−0.095 ***	−0.230	−0.324 **	Table A9
Alternative matrix: $W_{PGDP}^3_{ij}$	−0.107 ***	−0.146 **	−0.064	−0.104 ***	−0.129 **	−0.234 ***	Table A10
Dynamic SDM	−0.0131	−0.0224	0.017	−0.014 *	−0.023 *	−0.036 ***	Table A11

Table 7. Cont.

(b)			
	(1)	(2)	(3)
	Panel A: Parameter results (<i>CEI_EDGAR</i>)		
	Main (β)	WX (θ)	Spatial
<i>REG_share</i>	−3.126 *** (0.613)	−0.431 (0.904)	
<i>REG_share</i> ²	2.192 *** (0.545)	−1.893 ** (0.924)	
<i>lnPGDP</i>	−0.871 *** (0.199)	1.493 *** (0.380)	
<i>Urban</i>	−4.718 *** (0.898)	−9.384 *** (1.649)	
<i>Indst</i>	0.405 *** (0.0838)	0.130 (0.172)	
<i>EnvirReg</i>	6.328 (7.794)	−7.331 (15.960)	
Rho (ρ)			−0.240 *** (0.058)
R ²	0.417	0.417	0.417
Observations	600	600	600
Number of provinces	30	30	30
Province fixed	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes
Panel B: Direct, indirect and total effect (<i>CEI_EDGAR</i>)			
	Direct	Indirect	Total
<i>REG_share</i>	−3.121 *** (0.670)	0.280 (0.857)	−2.841 *** (0.548)
<i>REG_share</i> ²	2.296 *** (0.592)	−2.089 ** (0.835)	0.207 (0.614)
<i>lnPGDP</i>	−0.942 *** (0.190)	1.484 *** (0.328)	0.542 (0.336)
<i>Urban</i>	−4.319 *** (0.909)	−7.103 *** (1.436)	−11.420 *** (1.368)
<i>Indst</i>	0.404 *** (0.081)	0.0286 (0.136)	0.433 *** (0.166)
<i>EnvirReg</i>	7.157 (7.796)	−7.026 (14.200)	0.131 (14.990)
R ²	0.417	0.417	0.417
Observations	600	600	600
Number of provinces	30	30	30
Province fixed	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes

(a) Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *REG_share* and *lnREG* denote REG. *CEI_EDGAR*, *CEI_IPCC* and *CEI_apparent* denote CEI. The table summarizes the main SDM robustness results by reporting the main coefficient, spatially lagged coefficient, spatial autoregressive coefficient, and the direct, indirect, and total effects of REG. All specifications include the baseline control variables and province and year fixed effects; the Region $\times$ Year FE specification replaces year fixed effects with region-by-year fixed effects. Two alternative spatial weight matrices $W_{distance_{ij}^2}$ and $W_{PGDP_{ij}^3}$ are also employed to replace $W_{neighbor_{ij}^1}$. Full estimation results are reported in Appendix D, Tables A4–A11. (b) Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$. *REG_share* denotes REG. *CEI_EDGAR* denotes CEI. Panel A shows the analysis of SDM results. Panel B shows the decomposition of SDM effects, including direct, indirect and total effect.

(2) SDM: Nonlinear effects of REG

The preceding analysis assumes that the association between REG and CEI is linear. However, the decoupling results suggest that the REG–CEI relationship has evolved over time, and the marginal mitigation association of renewable electricity may not remain constant as renewable electricity penetration increases. In particular, when the share of renewable electricity is relatively low, additional renewable electricity may replace fossil-based electricity more directly and generate larger carbon-intensity improvements. As renewable penetration rises, however, grid integration constraints, renewable curtail-

ment, storage limitations, and the declining substitution space for fossil electricity may weaken the marginal mitigation association. Therefore, this study adds the squared term of *REG_share* to the SDM specification to examine whether the REG-CEI relationship exhibits nonlinear characteristics.

Table 7b reports the nonlinear SDM results. The coefficient of *REG_share* is significantly negative, while the coefficient of its squared term is significantly positive. This provides evidence consistent with a diminishing marginal mitigation pattern: renewable electricity penetration is associated with lower CEI, but the marginal association becomes weaker as the renewable electricity share increases. Economically, this finding implies that expanding renewable electricity capacity alone may not be sufficient once renewable penetration reaches a higher level. To sustain the carbon-intensity mitigation association of REG, renewable electricity expansion needs to be accompanied by improvements in grid flexibility, storage capacity, interprovincial transmission, and electricity-market mechanisms that support effective renewable electricity consumption.

Overall, these robustness checks indicate that the baseline association between REG and CEI is not driven by a specific sample period, carbon accounting method, spatial weight matrix, fixed-effect structure, or dynamic specification. In addition, the mitigation association of REG may weaken at higher levels of renewable electricity penetration, highlighting the importance of grid integration and effective renewable electricity consumption.

4.2.3. Endogeneity Issue

Potential endogeneity may arise from reverse causality, omitted variables, measurement errors, and policy selection. Provinces with lower CEI or stronger low-carbon transition capacity may be more likely to develop REG, while unobserved factors such as renewable resource endowments, grid infrastructure, policy intensity, and industrial upgrading may affect both REG and CEI. Therefore, this section conducts supplementary IV tests to assess the reliability of the baseline association. These tests are not interpreted as definitive causal identification.

(1) Supplementary lagged REG IV test

To partially mitigate the endogeneity issue, this study adopts the lagged values of REG as instrumental variables (IV) and applies a two-stage least squares (2SLS) estimation [54]. The use of lagged explanatory variables as instruments is well established in the empirical literature, particularly in studies examining energy, environment, and economic relationships, where lagged terms are commonly used to help address endogeneity concerns [55–57]. The rationale is that past REG is strongly correlated with current REG, while it is less likely to be affected by contemporaneous shocks to current CEI. However, lagged variables may still be correlated with persistent unobserved provincial characteristics. Therefore, this test is used as a supplementary internal-IV check rather than a primary identification strategy.

Table 8a reports the 2SLS results using lagged REG as the IV. The first-stage coefficients of *L.REG_share* and *L.InREG* are positive and significant, indicating strong persistence in REG. The diagnostic tests further support instrument relevance. In Panel A, the *KP rk Wald F* statistics are far above conventional weak-instrument thresholds, and the *KP rk LM* statistics reject the null of underidentification. The Anderson–Rubin Wald tests are also statistically significant, providing additional support for the second-stage association under weak-instrument-robust inference. In Panel B, the *KP rk Wald F* and *KP rk LM* statistics also support instrument relevance, although the Anderson–Rubin tests are weaker for some CEI measures. Overall, the lagged-IV results are broadly consistent with the baseline findings and provide supplementary evidence that REG is associated with lower CEI.

Table 8. (a) Endogeneity test: 2SLS regression using lagged one period *REG*. (b) Endogeneity test: 2SLS regression using external climate-geography instruments.

(a)				
Panel A: lagged <i>REG_share</i> as instrumental variable				
	(1) <i>REG_share</i>	(2) <i>CEI_EDGAR</i>	(3) <i>CEI_IPCC</i>	(4) <i>CEI_apparent</i>
<i>L.REG_share</i>	0.819 *** (0.036)			
<i>REG_share</i>		−1.613 ** (0.740)	−2.481 *** (0.680)	−3.589 *** (1.375)
Controls	Yes	Yes	Yes	Yes
Constant	0.791 *** (0.251)	12.300 ** (6.091)	8.053 (8.653)	24.060 (15.720)
R ²	0.980	0.958	0.965	0.932
Observations	570	570	480	510
Province fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
<i>KP rk Wald F</i>		467.079	124.607	184.540
<i>KP rk LM</i>		9.546 ***	6.500 **	7.328 ***
Anderson – Rubin Wald F		4.730 **	15.500 ***	7.69 ***
Panel B: lagged <i>lnREG</i> as instrumental variable				
	(1) <i>lnREG</i>	(2) <i>CEI_EDGAR</i>	(3) <i>CEI_IPCC</i>	(4) <i>CEI_apparent</i>
<i>L.lnREG</i>	0.850 *** (0.029)			
<i>lnREG</i>		−0.116 ** (0.057)	−0.063 (0.046)	−0.104 (0.070)
Controls	Yes	Yes	Yes	Yes
Constant	12.540 *** (3.877)	16.030 *** (5.562)	11.040 (9.350)	27.620 * (16.670)
R ²	0.966	0.957	0.960	0.928
Observations	570	570	480	510
Province fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
<i>KP rk Wald F</i>		743.752	423.540	529.372
<i>KP rk LM</i>		11.768 ***	11.244 ***	11.471 ***
Anderson – Rubin Wald F		3.620 *	1.65	1.93
(b)				
	(1) <i>REG_share</i>	(2) <i>CEI_apparent</i>	(3) <i>REG_share</i>	(4) <i>CEI_apparent</i>
<i>Wind × lnRain</i>	0.011 *** (0.003)			
<i>REG_share</i>		−12.900 ** (5.578)		
<i>Terrain × (Wind + lnRain)</i>			0.027 ** (0.013)	
<i>REG_share</i>				−10.730 * (5.868)
Controls	Yes	Yes	Yes	Yes
Constant	0.676 (0.881)	21.690 (16.110)	0.764 (0.864)	21.140 (14.620)
R ²	0.949	0.881	0.949	0.899
Observations	600	540	600	540
Province fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
<i>KP rk Wald F</i>	6.955		3.526	
<i>KP rk LM</i>	6.250 **		7.067 ***	
Anderson – Rubin Wald F		5.910 **		2.300

(a) Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *REG_share* and *lnREG* denote REG. *CEI_EDGAR*, *CEI_IPCC*, and *CEI_apparent* denote CEI. *L.REG_share* and *L.lnREG* denote REG for lagging one period. Panel A shows the results of using *L.REG_share* as IV. Panel B shows the results of using *L.lnREG* as IV. The Kleibergen–Paap rk Wald F statistic (*KP rk Wald F*) is used to assess weak-instrument concerns. The Kleibergen–Paap rk LM statistic (*KP rk LM*) is used to test underidentification. The Anderson–Rubin Wald F statistic is reported for weak-instrument-robust inference. (b) Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *REG_share* denotes REG. *CEI_apparent* denotes CEI. *Wind × lnRain* denotes the interaction term of wind speed and the logarithm of precipitation. *Terrain × (Wind + lnRain)* denotes the interaction between terrain relief and the combined annual wind-speed and precipitation conditions. The Kleibergen–Paap rk Wald F statistic (*KP rk Wald F*) is used to assess weak-instrument concerns. The Kleibergen–Paap rk LM statistic (*KP rk LM*) is used to test underidentification. The Anderson–Rubin Wald F statistic is reported for weak-instrument-robust inference.

(2) Supplementary external climate-geography IV tests

In addition, this study further constructs external IV based on climate and geographical renewable-resource conditions. Existing research shows that wind speed can provide exogenous variation in wind electricity generation [58], and that the environmental effects of renewable electricity depend on resource conditions, electricity-system constraints, and geographical factors [59]. Accordingly, $Wind \times \ln Rain$ is used to capture the joint annual availability of wind and hydrological resources, while $Terrain \times (Wind + \ln Rain)$ combines terrain relief with annual wind speed and precipitation conditions to reflect the interaction between long-term geographical suitability and time-varying renewable-resource availability. The rationale is that wind speed is closely related to wind-power generation potential, precipitation affects hydropower availability, and terrain relief is associated with hydropower development conditions and the geographical feasibility of REG. These variables therefore provide plausibly exogenous variation in REG related to renewable-resource conditions, although the exclusion restriction cannot be fully verified with province-level data.

Table 8b reports the 2SLS results using these external climate-geography Ivs. The first-stage results show that both instruments are positively associated with REG_share , and the $KP\ rk\ LM$ statistics reject the null of underidentification, suggesting that the instruments are correlated with REG. The second-stage coefficients of REG_share remain negative when $CEI_apparent$ is used as the dependent variable, which is directionally consistent with the baseline results. However, the $KP\ rk\ Wald\ F$ statistics are relatively low, especially for $Terrain \times (Wind + \ln Rain)$, indicating that weak-instrument concerns may remain. Therefore, the external-IV results are interpreted cautiously as supplementary evidence rather than definitive evidence of causality.

4.2.4. Heterogeneity Analysis

The heterogeneity analysis further examines whether the REG-CEI association differs across provinces with different positions in China's electricity geography. This section interprets heterogeneity from a demand-side and supply-side perspective. Eastern and high-CEI provinces are more closely related to the demand-side substitution logic, where industrial and electricity demand is concentrated and renewable electricity can more directly replace fossil-based electricity consumption. By contrast, western, northeastern, and resource-based provinces are more closely related to the supply-side and spatial spillover logic, where renewable resources and electricity generation bases are more concentrated but local absorption capacity is relatively limited, making interprovincial transmission and spatial reallocation more important.

(1) Regional heterogeneity in local and spatial effects

The regional heterogeneity results in Table 9a show clear differences across eastern, central, western, and northeastern China. The coefficient of REG is largest and most significant in the eastern region, suggesting that the local mitigation association is strongest in economically developed and electricity-demand-intensive provinces. This finding is consistent with the demand-side substitution logic. Eastern provinces have higher industrial and electricity demand, more developed power markets, and stronger capacity to absorb green electricity. Therefore, an increase in renewable electricity penetration may be more directly associated with fossil-based electricity substitution and lower local carbon intensity.

Table 9. (a) SDM regional heterogeneity analysis using $W_neighbor_{ij}^1$. (b) SDM resource endowment heterogeneity analysis using $W_neighbor_{ij}^1$. (c) SDM CEI heterogeneity analysis using $W_neighbor_{ij}^1$.

(a)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Eastern		Central		Western		Northeastern	
	CEI_EDGAR		CEI_EDGAR		CEI_EDGAR		CEI_EDGAR	
REG_share	−2.618 ***		−0.667 *		−0.613 *		−0.270	
	(0.395)		(0.396)		(0.360)		(0.470)	
lnREG		−0.121 ***		−0.055		−0.113 **		−0.134 ***
		(0.016)		(0.037)		(0.049)		(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
WX (θ)	−0.105	0.071 ***	−1.311	−0.255 ***	0.969	−0.475 ***	−0.347	−0.167 ***
	(0.687)	(0.023)	(0.818)	(0.089)	(0.762)	(0.105)	(0.516)	(0.038)
Rho (ρ)	−0.040	0.031	−0.023	−0.079	−0.835 ***	−0.873 ***	−0.243 **	−0.368 ***
	(0.081)	(0.081)	(0.117)	(0.119)	(0.092)	(0.092)	(0.107)	(0.088)
R ²	0.710	0.634	0.706	0.655	0.218	0.033	0.660	0.639
Observations	200	200	120	120	220	220	60	60
Number of provinces	10	10	6	6	11	11	3	3
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
(b)								
	(1)	(2)	(3)	(4)				
	Resource-based		Non-resource-based					
	CEI_EDGAR		CEI_EDGAR					
REG_share	−0.901 ***		−2.618 ***					
	(0.303)		(0.395)					
lnREG		−0.152 ***		−0.121 ***				
		(0.036)		(0.016)				
Controls	Yes	Yes	Yes	Yes				
WX (θ)	−1.819 ***	−0.330 ***	−0.105	0.031				
	(0.538)	(0.068)	(0.687)	(0.081)				
Rho (ρ)	−0.641 ***	−0.644 ***	−0.040	0.071 ***				
	(0.074)	(0.074)	(0.083)	(0.023)				
R ²	0.018	0.263	0.710	0.634				
Observations	400	400	200	200				
Number of provinces	20	20	10	10				
Province fixed	Yes	Yes	Yes	Yes				
Year fixed	Yes	Yes	Yes	Yes				
(c)								
	(1)	(2)	(3)	(4)				
	High CEI		Low CEI					
	CEI_EDGAR		CEI_EDGAR					
REG_share	−2.812 ***		−1.305 ***					
	(0.497)		(0.158)					
lnREG		−0.003		−0.027 **				
		(0.028)		(0.012)				
Controls	Yes	Yes	Yes	Yes				
WX (θ)	1.596 ***	−0.001	0.530 **	0.094 ***				
	(0.607)	(0.057)	(0.210)	(0.014)				
Rho (ρ)	−0.394 ***	−0.425 ***	−0.257 ***	−0.102 *				
	(0.067)	(0.067)	(0.053)	(0.057)				
R ²	0.246	0.086	0.858	0.756				
Observations	200	200	200	200				
Number of provinces	15	15	15	15				
Province fixed	Yes	Yes	Yes	Yes				
Year fixed	Yes	Yes	Yes	Yes				

(a) Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *REG_share* and *lnREG* denote REG. *CEI_EDGAR* denotes CEI. (b) Notes: Standard errors in parentheses. *** $p < 0.01$. *REG_share* and *lnREG* denote REG. *CEI_EDGAR* denotes CEI. (c) Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *REG_share* and *lnREG* denote REG. *CEI_EDGAR* denotes CEI.

By contrast, the spatial effects are more pronounced in western and northeastern regions. The spatial autoregressive coefficient is insignificant in the eastern region but significantly negative in western and northeastern regions, indicating that CEI in these regions is more closely linked to interregional interactions. This pattern reflects the supply-side role of these regions in China's electricity system. Western and northeastern provinces often have richer renewable resources and serve as important electricity generation and transmission bases, but their local electricity demand and absorption capacity are relatively limited. As a result, the carbon-intensity implications of REG in these regions are more likely to operate through interprovincial transmission, spatial reallocation of electricity supply, and interactions with neighboring provinces. Overall, the regional results suggest that REG mainly operates through local demand-side substitution in eastern provinces, while it works more through supply-side spillovers and spatial transmission in western and northeastern provinces.

(2) Resource endowment heterogeneity in local and spatial effects

The resource endowment heterogeneity results in Table 9b further support the supply-side interpretation. Resource-based provinces in this study include Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang, while non-resource-based provinces include Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. REG is significantly associated with lower CEI in both resource-based and non-resource-based provinces, indicating that the local mitigation association is not limited to one type of region. However, the spatially lagged REG term is significantly negative only in resource-based provinces, suggesting that spatial spillover effects are stronger in regions with heavier resource dependence and deeper participation in interregional energy supply networks.

This result can be explained by the role of resource-based provinces in China's energy system. Many of these provinces are traditional fossil-energy bases and are also important locations for renewable electricity development. Their energy production, industrial structure, and electricity transmission are more closely connected with surrounding regions. Therefore, renewable electricity expansion in resource-based provinces may be linked to neighboring regions through power transmission, energy supply-chain adjustment, and the relocation or upgrading of energy-intensive industries. In contrast, non-resource-based provinces are more likely to be electricity-consuming regions, where the association of REG with CEI is reflected more in local substitution than in spatial transmission. These findings indicate that resource endowments shape not only the local association of REG with lower CEI but also the strength of its cross-regional spillover associations.

(3) Carbon emission intensity heterogeneity in local and spatial effects

Table 9c reports the heterogeneity results for high- and low-CEI provinces. The coefficient of REG is significantly negative in both groups, but its magnitude is larger in high-CEI provinces. This suggests that the mitigation association of renewable electricity is stronger where carbon intensity is initially higher. The result is consistent with the demand-side substitution logic because high-CEI provinces usually have heavier industrial structures, stronger fossil-energy dependence, and greater room for replacing carbon-intensive electricity with renewable electricity. In these provinces, an increase in renewable electricity penetration may be associated with larger marginal improvements in carbon efficiency.

However, the spatial transmission pattern is not identical across high- and low-CEI provinces. High-CEI provinces are often embedded in fossil-energy and heavy-industrial systems, which makes their local carbon-intensity improvement more closely related to energy-structure adjustment and industrial upgrading. Low-CEI provinces, by contrast,

may have relatively cleaner industrial structures and less room for marginal reduction. Therefore, the stronger coefficient in high-CEI provinces indicates that REG is especially important for regions where the potential for fossil-energy substitution is larger.

Taken together, the heterogeneity results reveal a consistent economic logic. Eastern and high-CEI provinces mainly reflect demand-side substitution effects, because renewable electricity can be more directly absorbed and used to replace fossil-based electricity consumption. Western, northeastern, and resource-based provinces mainly reflect supply-side and spatial spillover effects, because REG is more closely linked to resource endowments, transmission networks, and interregional electricity allocation. Therefore, the REG–CEI association depends not only on REG itself, but also on whether renewable electricity can be consumed locally, transmitted efficiently, and integrated into regional industrial and electricity systems.

4.2.5. Mechanism Analysis

The previous results show that REG is significantly associated with lower CEI and that this association differs across regions. To further explain the possible channels behind this relationship, this section examines three mechanism-related pathways: the moderating role of ER, the mediating role of ES, and the mediating role of EI [3,23]. Conceptually, ER represents the policy-pressure channel, ES captures the energy-substitution channel, and EI reflects the energy-efficiency channel. Specifically, stronger ER may increase the cost of fossil-energy use and strengthen the incentive to consume renewable electricity; ES optimization may be associated with lower CEI through a lower share of coal and other carbon-intensive energy sources; and EI improvement may be associated with lower CEI through lower energy requirements per unit of economic output. These mechanisms are not interpreted as definitive evidence of causality, but as evidence consistent with possible transmission channels through which REG may be associated with lower CEI.

Due to data availability, ES and EI are no longer officially reported after 2020. Therefore, this study uses a balanced panel dataset covering the period from 2005 to 2019 to conduct the mediation tests. To examine the moderating effect of ER and the mediating effects of ES and EI, the corresponding SDM specifications are presented in Equations (12)–(14).

$$CEI_{it} = \rho \sum_{j \neq i}^{30} w_{ij} CEI_{jt} + \beta_1 REG_{it} + \beta_2 EnvirReg_{it} + \beta_3 REG_{it} \times EnvirReg_{it} + \theta_1 \sum_{j \neq i}^{30} w_{ij} REG_{jt} + \theta_2 \sum_{j \neq i}^{30} w_{ij} EnvirReg_{jt} + \theta_3 \sum_{j \neq i}^{30} w_{ij} REG_{jt} \times EnvirReg_{jt} + \delta_1 Controls_{it} + \eta_1 \sum_{j \neq i}^{30} w_{ij} Controls_{jt} + \mu_i + \gamma_t + \xi_{it} \quad (12)$$

$$M_{it} = \rho_m \sum_{j \neq i}^{30} w_{ij} M_{jt} + \beta_m REG_{it} + \theta_m \sum_{j \neq i}^{30} w_{ij} REG_{jt} + \delta_m Controls_{it} + \eta_m \sum_{j \neq i}^{30} w_{ij} Controls_{jt} + \mu_i + \gamma_t + \nu_{it} \quad (13)$$

$$CEI_{it} = \rho \sum_{j \neq i}^{30} w_{ij} CEI_{jt} + \beta' REG_{it} + \theta' \sum_{j \neq i}^{30} w_{ij} REG_{jt} + \varphi M_{it} + \omega \sum_{j \neq i}^{30} w_{ij} M_{jt} + \delta' Controls_{it} + \eta' \sum_{j \neq i}^{30} w_{ij} Controls_{jt} + \mu_i + \gamma_t + \xi_{it} \quad (14)$$

where, in Equation (12), $REG_{it} \times EnvirReg_{it}$ is the interaction term. β_3 captures the moderating effect of ER. The fixed effects are defined consistently with the baseline specification. In Equation (13), M_{it} denotes the mediating variable, including ES or EI. The parameter ρ_m captures the spatial dependence of the mediating variable. The coefficients β_m and θ_m measure the direct and spatial spillover effects of REG on the mediating variable, respectively. In Equation (14), φ measures the direct effect of the mediating variable, while ω captures its spatial spillover effect. The control variables and fixed effects are defined consistently with the baseline specification.

Because the SDM framework allows both local and spatial spillover channels, the mechanism analysis reports direct, indirect, and total effects where appropriate. The direct

effect captures the local mechanism within a province, while the indirect effect reflects spatial transmission across neighboring provinces.

(1) Moderating effect of ER

Table 10a reports the moderating effect of ER. In Panel A, the interaction term between REG and ER is significantly negative, providing evidence consistent with the view that ER strengthens the negative association between REG and CEI. Economically, this result suggests that renewable electricity penetration is more closely associated with lower CEI when environmental regulatory pressure is stronger. Stricter ER can increase the relative cost of carbon-intensive production and fossil-energy use, thereby encouraging firms and local governments to substitute fossil-based electricity with cleaner electricity. In this sense, ER may strengthen the REG-CEI association by improving the institutional and policy conditions under which renewable electricity is consumed and integrated into the energy system.

Table 10. (a) Panel A. SDM moderation test: ER using $W_neighbor_{ij}^1$. Panel B. SDM moderation test: ER using $W_neighbor_{ij}^1$ (EnvirReg). (b) Panel A. SDM mediation test: ES using $W_neighbor_{ij}^1$ (ES). Panel B. SDM mediation test: ES using $W_neighbor_{ij}^1$ (ES). (c) Panel A. SDM mediation test: EI using $W_neighbor_{ij}^1$ (EI). Panel B. SDM mediation test: EI using $W_neighbor_{ij}^1$ (EI).

(a)				
Panel A: Parameter results (CEI_EDGAR)				
	(1) Main (β)	(2) WX (θ)	(3) Main (β)	(4) WX (θ)
REG_share	−0.963 *** (0.293)	−2.375 *** (0.496)	−0.790 *** (0.292)	−2.366 *** (0.500)
EnvirReg	4.127 (7.880)	−4.178 (15.750)	28.870 *** (9.748)	−13.860 (19.710)
REG_share × EnvirReg			−112.700 *** (26.810)	22.670 (49.700)
Controls	Yes	Yes	Yes	Yes
Rho (ρ)	−0.230 *** (0.058)		−0.241 *** (0.058)	
R ²	0.338	0.338	0.400	0.400
Observations	600	600	600	600
Number of provinces	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
Panel B: Direct, indirect and total effect (CEI_EDGAR)				
	(1) Direct	(2) Indirect	(3) Total	
REG_share	−0.661 ** (0.313)	−1.873 *** (0.457)	−2.534 *** (0.357)	
EnvirReg	29.650 *** (9.693)	−18.080 (17.640)	11.560 (17.220)	
REG_share × EnvirReg	−112.900 *** (26.560)	45.650 (43.820)	−67.240 (44.150)	
Controls	Yes	Yes	Yes	
R ²	0.400	0.400	0.400	
Observations	600	600	600	
Number of provinces	30	30	30	
Province fixed	Yes	Yes	Yes	
Year fixed	Yes	Yes	Yes	

Table 10. Cont.

(b)					
Panel A: Parameter results (<i>CEI_IPCC</i> and <i>CEI_apparent</i>)					
	(1)	(2)	(3)	(4)	(5)
	<i>CEI_IPCC</i>	<i>CEI_apparent</i>	<i>ES</i>	<i>CEI_IPCC</i>	<i>CEI_apparent</i>
<i>REG_share</i>	−1.870 *** (0.384)	−2.448 *** (0.781)	−0.299 *** (0.082)	−1.682 *** (0.391)	−1.773 ** (0.790)
<i>ES</i>				0.546 ** (0.221)	1.004 ** (0.449)
Controls	Yes	Yes	Yes	Yes	Yes
WX (θ)	−1.772 *** (0.657)	−2.791 ** (1.340)	0.522 *** (0.138)	−1.993 *** (0.672)	−2.293 * (1.359)
Rho (ρ)	−0.069 (0.070)	−0.061 (0.084)	0.360 *** (0.058)	−0.079 (0.071)	−0.062 (0.084)
R ²	0.188	0.108	0.034	0.249	0.158
Observations	450	450	450	450	450
Number of provinces	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes
Panel B: Direct, indirect and total effect (<i>CEI_IPCC</i>)					
			(1)	(2)	(3)
			Direct	Indirect	Total
<i>REG_share</i>			−1.632 *** (0.404)	−1.758 *** (0.616)	−3.390 *** (0.540)
<i>ES</i>			0.548 ** (0.216)	−0.446 (0.364)	0.102 (0.325)
Controls			Yes	Yes	Yes
R ²			0.249	0.249	0.249
Observations			450	450	450
Number of provinces			30	30	30
Province fixed			Yes	Yes	Yes
Year fixed			Yes	Yes	Yes
(c)					
Panel A: Parameter results (<i>CEI_IPCC</i> and <i>CEI_apparent</i>)					
	(1)	(2)	(3)	(4)	(5)
	<i>CEI_IPCC</i>	<i>CEI_apparent</i>	<i>EI</i>	<i>CEI_IPCC</i>	<i>CEI_apparent</i>
<i>REG_share</i>	−1.870 *** (0.384)	−2.448 *** (0.781)	−0.409 ** (0.170)	−1.184 *** (0.208)	−2.013 *** (0.781)
<i>EI</i>				1.903 *** (0.057)	1.031 *** (0.214)
Controls	Yes	Yes	Yes	Yes	Yes
WX (θ)	−1.772 *** (0.657)	−2.791 ** (1.340)	−1.718 *** (0.299)	0.827 ** (0.388)	−0.891 (1.468)
Rho (ρ)	−0.069 (0.070)	−0.061 (0.084)	0.055 (0.064)	0.370 *** (0.059)	−0.033 (0.086)
R ²	0.188	0.108	0.091	0.874	0.300
Observations	450	450	450	450	450
Number of provinces	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes

Table 10. Cont.

Panel B: Direct, indirect and total effect (<i>CEI_IPCC</i>)			
	(1) Direct	(2) Indirect	(3) Total
<i>REG_share</i>	−1.138 *** (0.216)	0.568 (0.578)	−0.570 (0.640)
<i>EI</i>	1.847 *** (0.057)	−0.774 *** (0.168)	1.073 *** (0.196)
Controls	Yes	Yes	Yes
R ²	0.874	0.874	0.874
Observations	450	450	450
Number of provinces	30	30	30
Province fixed	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes

(a) Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$. *REG_share* and *lnREG* denote REG. *CEI_EDGAR* denotes CEI. Panel A shows the analysis of SDM results. Panel B shows the decomposition of SDM effects, including direct, indirect and total effect. (b) Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *REG_share* and *lnREG* denote REG. *CEI_IPCC* and *CEI_apparent* denote CEI. *ES* denotes energy structure (ES). Panel A shows the analysis of SDM results. Panel B shows the decomposition of SDM effects, including direct, indirect and total effect. (c) Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$. *REG_share* and *lnREG* denote REG. *CEI_IPCC* and *CEI_apparent* denote CEI. *EI* denotes energy intensity (EI). Panel A shows the analysis of SDM results. Panel B shows the decomposition of SDM effects, including direct, indirect and total effect.

Panel B further decomposes the moderating effect into direct, indirect, and total effects. The direct effect of the interaction term is significantly negative, indicating that the synergy between REG and ER is mainly reflected in a stronger local association with lower CEI. By contrast, the indirect effect is not statistically significant, suggesting that the moderating role of ER does not generate a strong spatial spillover effect. This is reasonable because ER is usually implemented and assessed within local administrative boundaries, while its enforcement intensity, policy design, and compliance pressure are more directly tied to local governments and local firms. Overall, the results provide evidence consistent with a local policy-synergy mechanism: ER strengthens the carbon-intensity mitigation association of REG mainly by reinforcing fossil-energy substitution within the same province.

(2) Mediating effect of ES

Table 10b reports the SDM mediation results for ES. In this study, ES is measured by the share of coal consumption in primary energy consumption; therefore, a lower value of ES reflects a cleaner energy structure. The mediator regression shows that REG is significantly negatively associated with ES, indicating that higher renewable electricity penetration is associated with a lower reliance on coal-based energy. This result is consistent with the energy-substitution mechanism: higher REG is associated with a lower share of carbon-intensive energy in the energy mix, thereby creating conditions for lower CEI.

When ES is included in the CEI equation, its coefficient is significantly positive, indicating that a more coal-intensive energy structure is associated with higher CEI. At the same time, the coefficient of REG remains negative but decreases in magnitude, providing evidence consistent with a partial mediation channel through ES. The effect decomposition in Panel B further shows that the direct effect of REG remains significantly negative, while the direct effect of ES is significantly positive. This suggests that the ES channel is mainly reflected in local energy-structure adjustment: renewable electricity expansion is associated with lower reliance on coal and other carbon-intensive energy sources within a province, which is linked to lower local CEI. The indirect effect of REG is also significantly negative, indicating that REG may generate spatial mitigation associations through interprovincial electricity transmission and regional energy-system adjustment. Overall, the ES results provide evidence consistent with the view that REG expansion is associated with a reduction

in coal dependence and an improvement in the energy structure, which in turn is linked to lower CEI.

(3) Mediating effect of EI

Table 10c presents the SDM mediation results for EI. EI captures the amount of energy consumed per unit of economic output, and therefore reflects the energy-efficiency channel. The mediator regression shows that REG is significantly negatively associated with EI, suggesting that renewable electricity development is accompanied by lower energy intensity. This may reflect cleaner electricity-system development, technological upgrading, improvements in energy-use efficiency, and the gradual replacement of energy-intensive production processes.

When EI is included in the CEI equation, its coefficient is significantly positive, indicating that higher energy intensity is associated with higher CEI. Meanwhile, the coefficient of REG remains negative but decreases in magnitude, providing evidence consistent with a partial mediation channel through EI. The decomposition results in Panel B show that the direct effect of REG remains significantly negative, while the direct and total effects of EI are significantly positive. This suggests that the EI mechanism mainly operates through local energy-efficiency improvement: REG is associated with lower energy use per unit of output, which in turn is associated with lower CEI. Although the indirect effect of EI is negative, the total effect remains positive, indicating that EI still represents an overall carbon-intensity-enhancing factor when energy use remains inefficient. Overall, the EI results provide evidence consistent with the view that REG expansion may be accompanied by a cleaner electricity system and improved energy efficiency, which is consistent with lower energy use per unit of GDP and lower CEI.

Taken together, the mechanism results provide a more coherent explanation of the REG-CEI association. ER strengthens the association mainly through local policy synergy, ES captures the substitution away from coal-intensive energy, and EI reflects improvements in energy-use efficiency. These findings suggest that REG is more closely associated with lower CEI when renewable electricity expansion is combined with stricter environmental governance, a cleaner energy structure, and lower energy intensity. These mechanism tests should be interpreted as evidence consistent with plausible transmission channels rather than as strict causal mediation estimates.

4.3. Summary of Empirical Findings

Overall, the empirical results provide consistent evidence on the relationship between REG and CEI in China. First, the descriptive and decoupling analyses show that the REG-CEI relationship has gradually shifted from weak decoupling to strong decoupling, suggesting that renewable electricity development has become increasingly associated with improvements in carbon efficiency over time. Second, the Moran's I results and spatial distribution maps reveal significant spatial clustering in CEI, indicating that provincial carbon intensity is not randomly distributed but shaped by regional structural conditions and spatial interactions. Third, the baseline spatial Durbin model (SDM) results show that REG is significantly associated with lower CEI, and the decomposition results further indicate that this association operates through both local and spillover channels. Fourth, the robustness and endogeneity tests provide support for the stability of the baseline findings, although the instrumental-variable results should be interpreted as supplementary evidence rather than definitive causal proof. Fifth, the heterogeneity results show that the local mitigation association is stronger in eastern and higher-CEI provinces, while spatial spillover associations are more pronounced in western, northeastern, and resource-based provinces. Finally, the mechanism analysis suggests that the REG-CEI association may partly operate through energy structure optimization and energy intensity reduction,

while environmental regulation may strengthen the mitigation association of REG. Taken together, these findings indicate that the carbon-intensity implications of REG are dynamic, spatially interconnected, regionally heterogeneous, and shaped by both structural and policy-related mechanisms.

5. Policy Implications and Limitations

Based on the above empirical findings, several policy implications can be drawn for sustainability-oriented energy policy. Because renewable electricity development is closely connected to carbon-intensity reduction, energy-structure optimization, energy-efficiency improvement, and regional coordination, the results provide practical implications for promoting a sustainable low-carbon energy transition in China. First, renewable electricity policy should shift from capacity expansion alone to effective consumption and system integration. In eastern and high-CEI provinces, where the local mitigation association is stronger, policy should focus on increasing the share of green electricity consumption. Local governments and grid enterprises can promote industrial electrification, expand distributed photovoltaic use in industrial parks and public buildings, encourage long-term green power purchase agreements, and strengthen the linkage between green electricity trading, green certificates, and carbon markets. These measures can help translate renewable electricity supply into actual carbon-intensity reduction on the demand side.

Second, for western and northeastern provinces, where spatial spillover associations are more pronounced, the priority should be cross-regional transmission and grid flexibility. Grid enterprises should improve interprovincial transmission capacity, alleviate renewable electricity curtailment, strengthen peak-shaving and energy storage systems, and better coordinate renewable electricity bases with receiving markets. In addition, interprovincial electricity pricing should more clearly reflect not only grid investment and operating costs, but also the carbon-reduction value of renewable electricity delivered to other regions. This would improve incentives for both renewable electricity exporting provinces and consuming provinces.

Third, resource-based provinces require a more differentiated transition strategy. These provinces should avoid a policy path in which renewable electricity expansion coexists with continued dependence on coal-based industries. Policy efforts should therefore combine renewable electricity development with the flexible transformation of coal power, industrial low-carbon upgrading, and stricter control of energy-intensive capacity. Renewable energy consumption responsibility weights should also be refined at the provincial level, taking into account renewable resource endowments, electricity demand, grid absorption capacity, industrial structure, and CEI. This would prevent uniform targets from placing excessive pressure on resource-exporting regions while ensuring that receiving provinces also bear responsibility for low-carbon electricity consumption.

Finally, differentiated assessment mechanisms should be established for local governments and grid enterprises. For local governments, evaluation indicators should move beyond installed renewable capacity and include renewable electricity consumption, curtailment alleviation, CEI improvement, EI improvement, and the share of green electricity in industrial electricity use. For grid enterprises, assessment should focus on renewable electricity integration capacity, interprovincial transmission efficiency, grid flexibility, storage coordination, and support for green electricity trading. These indicators would make policy implementation more consistent with the spatially differentiated associations identified in this study. Together, these policy measures can help transform renewable electricity expansion from a capacity-oriented strategy into a sustainability-oriented energy transition pathway that integrates carbon-intensity reduction, efficient energy use, and coordinated regional development.

This study also has several limitations. Although the empirical analysis provides supportive evidence on the association between REG and CEI, the study is not based on a natural experiment, and province-level panel data and instrumental variables cannot provide definitive causal proof. In addition, the 2024 wind and solar power generation data are estimated by interpolation and should therefore be interpreted with caution, although the robustness check excluding 2024 produces consistent results. Future research could use more refined grid-level electricity transmission data, renewable resource potential data, and firm- or city-level energy consumption information to provide stronger causal identification and more detailed practical validation.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EDGAR	Emissions Database for Global Atmospheric Research
CEADs	Carbon Emission Accounts and Datasets
REG	Renewable Electricity Generation
CEI	Carbon Emission Intensity
ES	Energy Structure
EI	Energy Intensity
ER	Environmental Regulation
SDM	Spatial Durbin Model
SLM	Spatial Lag Model

SEM	Spatial Error Model
OLS	Ordinary Least Squares
2SLS	Two-Stage Least Squares
IV	Instrumental Variables

Appendix A. Carbon Accounting Formulas

Following the sectoral accounting method [60], carbon emissions are first calculated by energy type and sector and then aggregated across all energy types and sectors to obtain total provincial CO₂ emissions, as shown in Equations (A1) and (A2). This approach provides a relatively detailed measure by accounting for sector-specific fossil fuel combustion.

$$CO_{2\text{ IPCC},\text{ }kjt} = AD_{\text{IPCC},kjt} \times NCV_k \times CC_k \times O_{kjt} \quad (\text{A1})$$

where $CO_{2\text{ IPCC},kjt}$ denotes the CO₂ emissions generated from energy type k in sector j in province i at time t ; $AD_{\text{IPCC},kjt}$ represents the activity data of fossil fuel consumption; NCV_k is the net calorific value of energy type k ; CC_k denotes the carbon content per unit of energy; and O_{kjt} is the oxidation factor.

$$CO_{2\text{ IPCC},\text{ }it} = \sum_k \sum_j CO_{2\text{ IPCC},\text{ }kjt} \quad (\text{A2})$$

where $CO_{2\text{ IPCC},it}$ represents total CO₂ emissions in province i at time t , obtained by aggregating emissions across all energy types and sectors.

The apparent accounting approach estimates provincial carbon emissions from apparent fossil fuel consumption, which is derived from the balance identity of indigenous production, imports, exports, inter-provincial inflows and outflows, stock changes, non-energy use, and losses, as shown in Equations (A3) and (A4) [61,62]. Compared with the sectoral approach, this method focuses more directly on the production-side balance of energy use.

$$AD_{\text{apparent},it} = \begin{aligned} & \text{indigenous production}_{it} + \text{imports}_{it} - \text{exports}_{it} \\ & + \text{moving in from other provinces}_{it} \\ & - \text{sending out to other provinces}_{it} \pm \text{stock change}_{it} \\ & - \text{non energy use}_{it} - \text{loss}_{it} \end{aligned} \quad (\text{A3})$$

where $AD_{\text{apparent},it}$ denotes apparent fossil fuel consumption in province i at time t , calculated based on the balance method including indigenous production, imports, exports, inter-provincial inflow and outflow, stock changes, non-energy use, and losses.

$$CO_{2\text{ apparent},\text{ }it} = AD_{\text{apparent},it} \times EF_k \quad (\text{A4})$$

where $CO_{2\text{ apparent},it}$ denotes CO₂ emissions calculated using the apparent energy consumption method, where EF_k is the emission factor. In Equations (A1)–(A4), i denotes the province, k represents the type of energy, j refers to the sector, and t indicates time.

Appendix B. Supplementary Figures

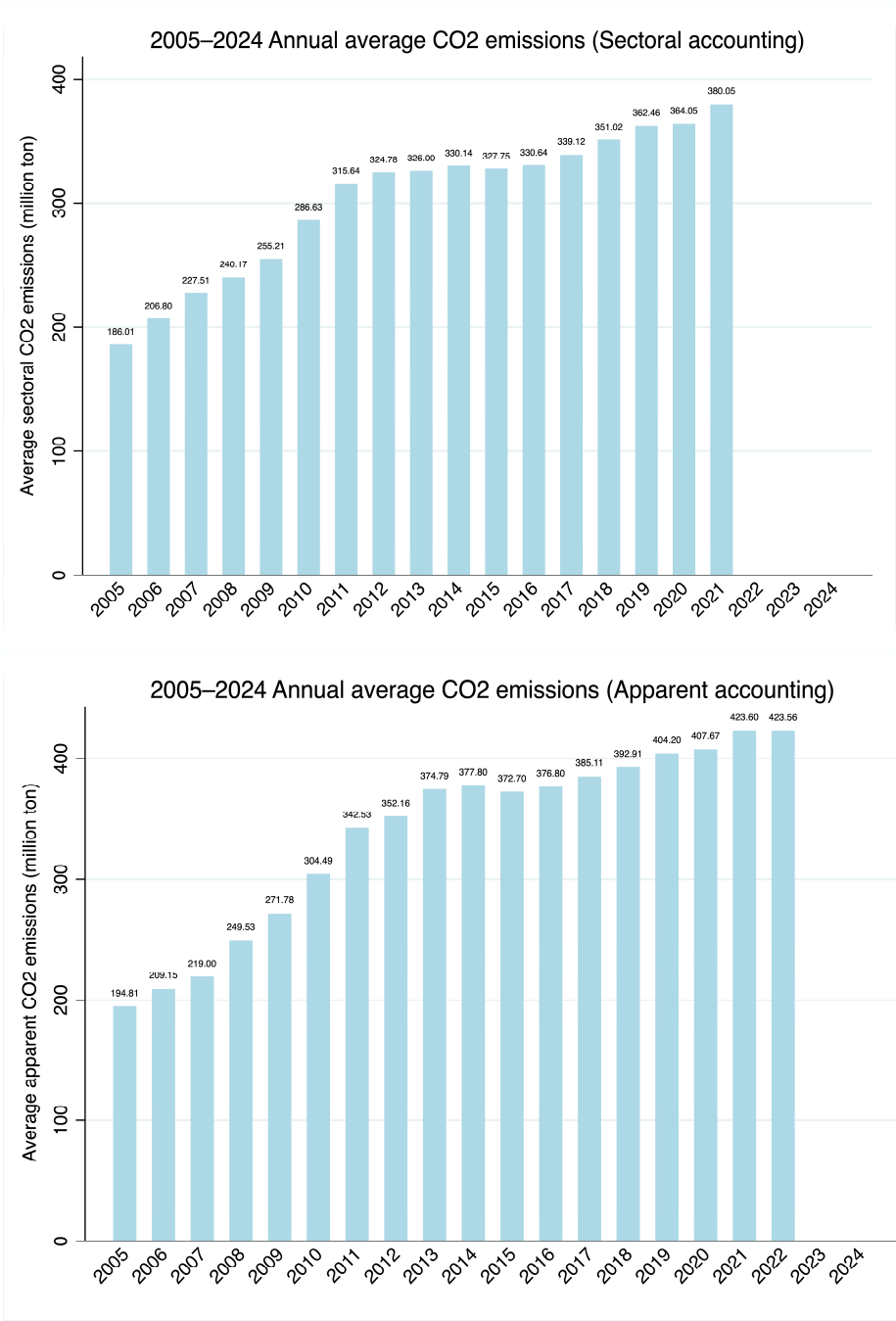


Figure A1. Cont.

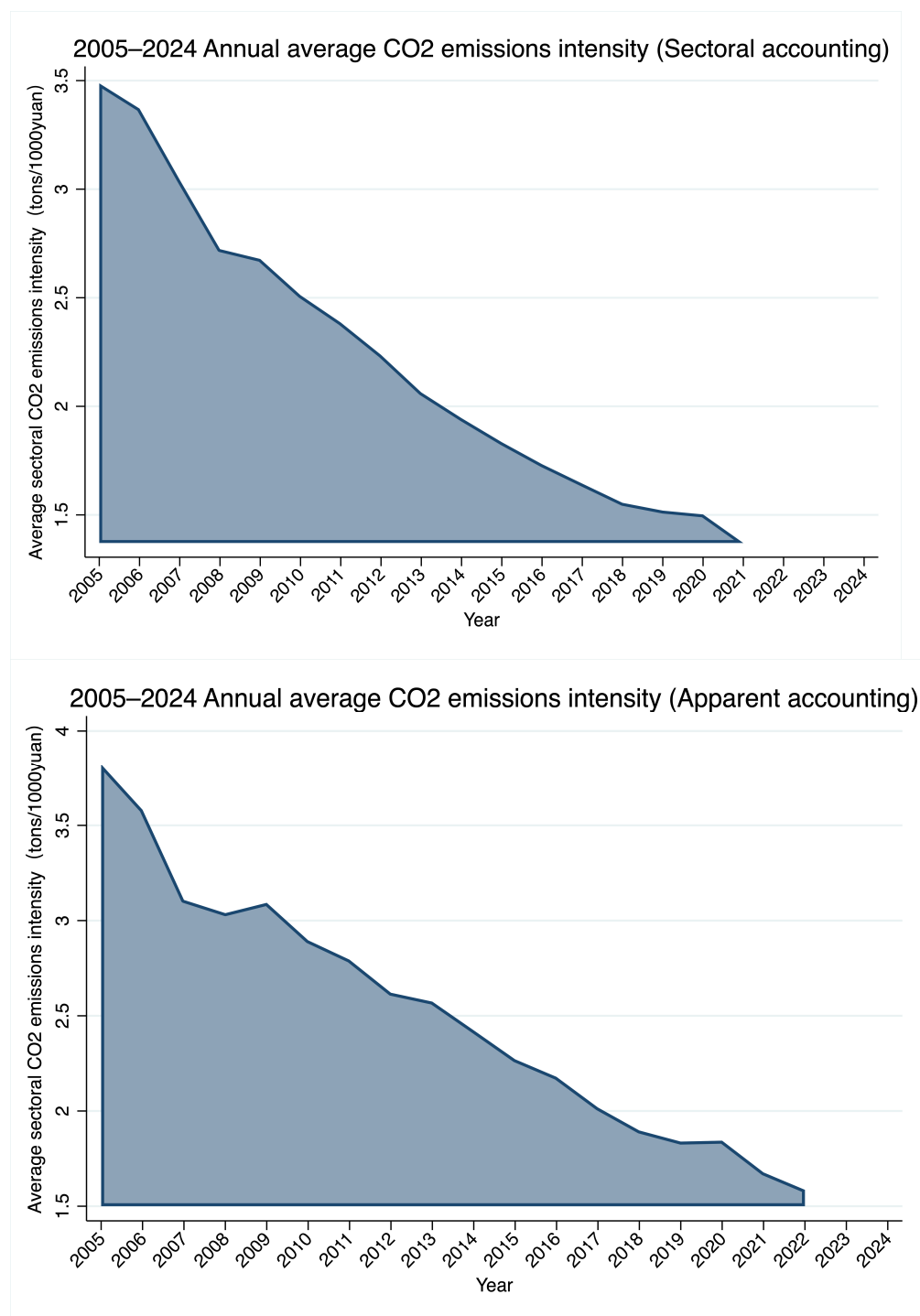


Figure A1. Annual average of carbon emissions and CEI using alternative measurements, 2005–2024.

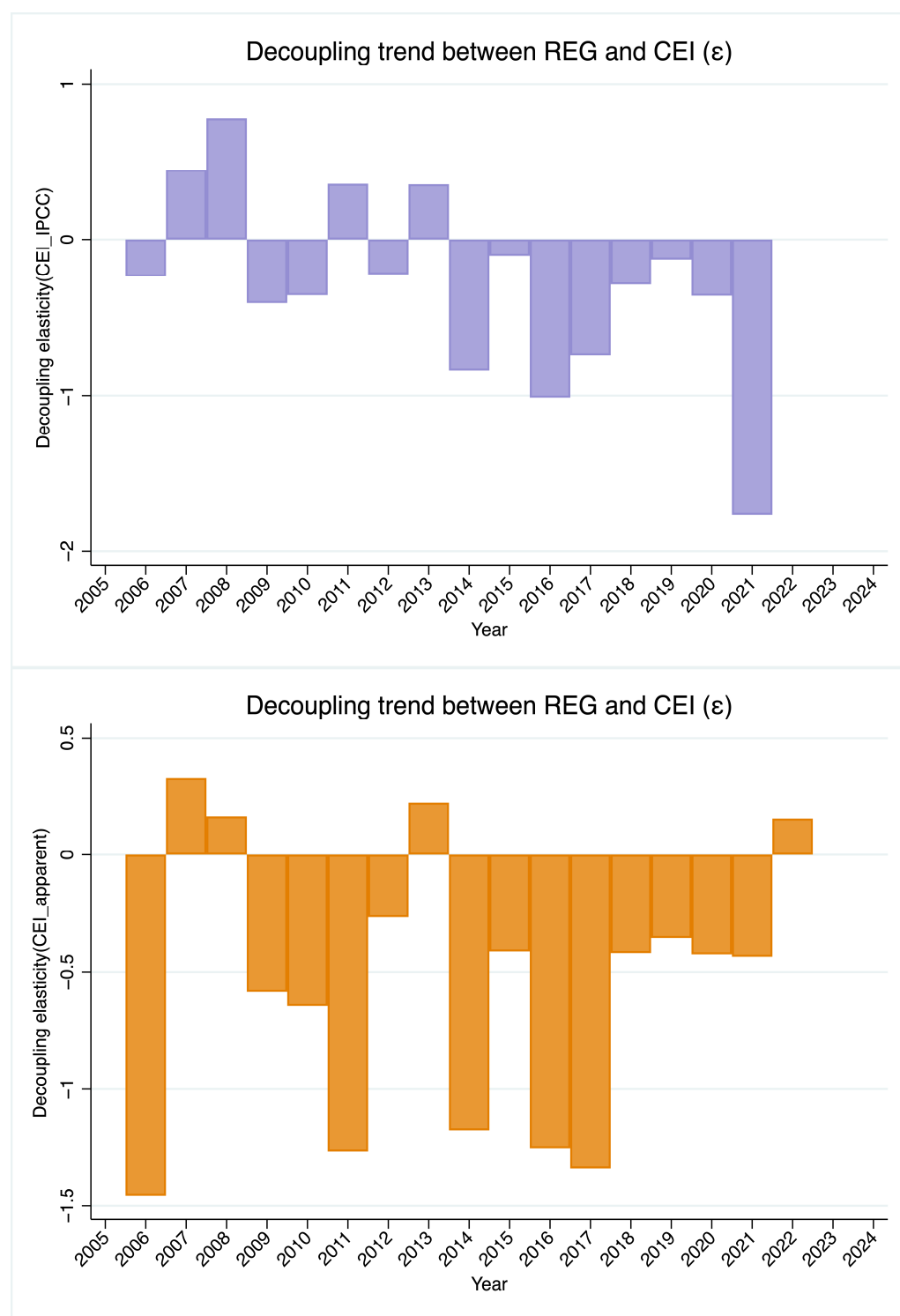


Figure A2. Decoupling trend between REG and CEI using alternative measurements, 2005–2024.

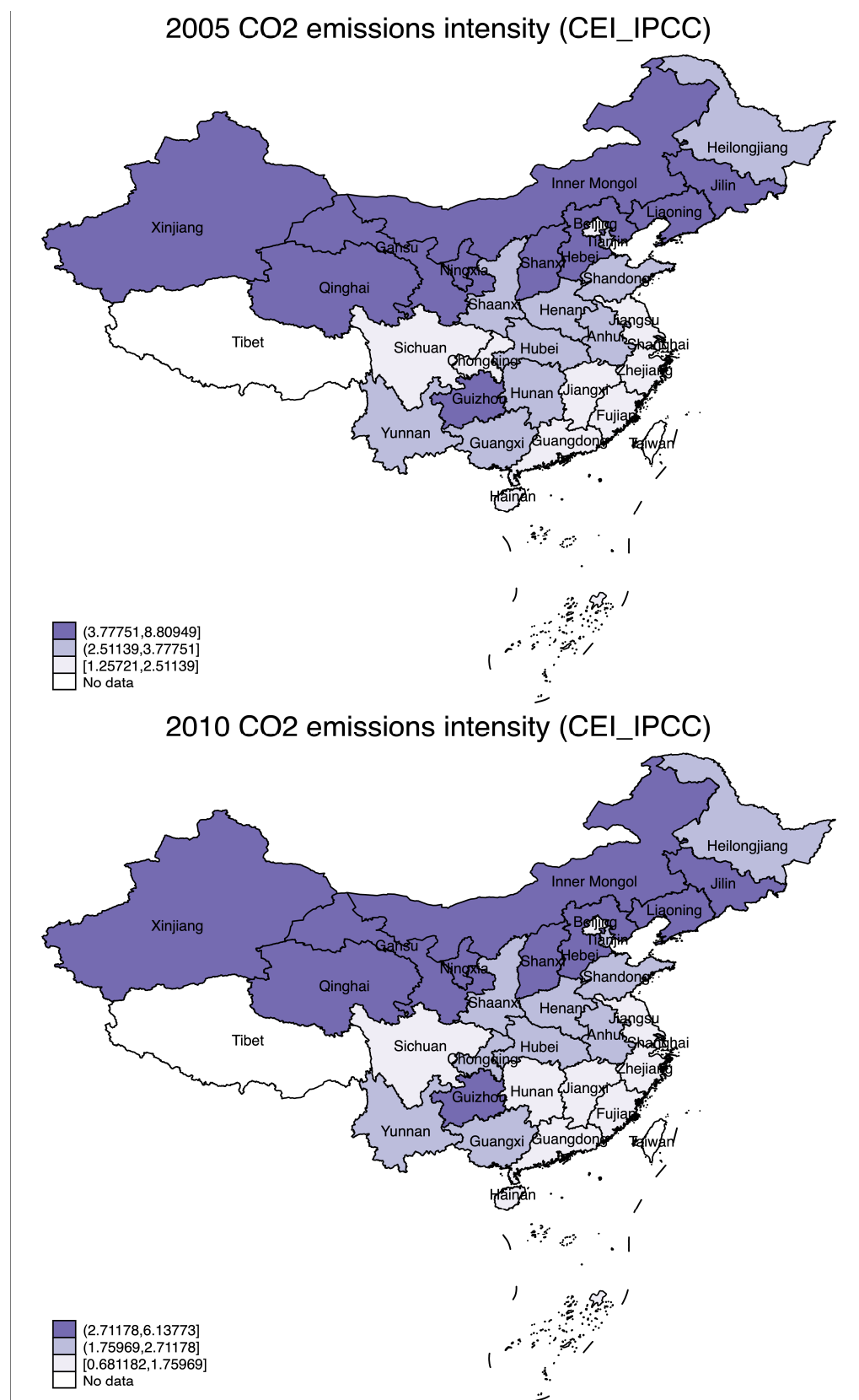


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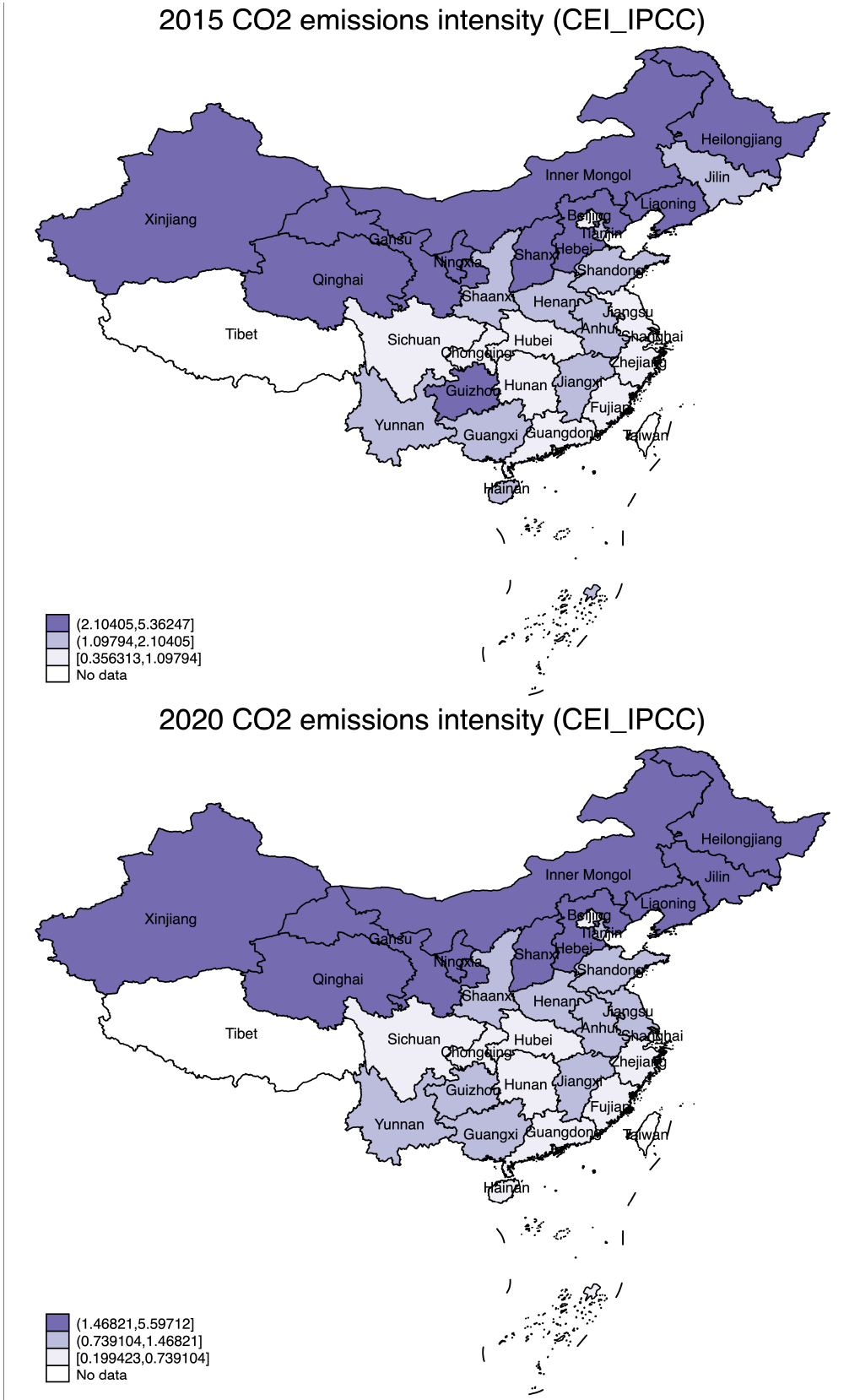


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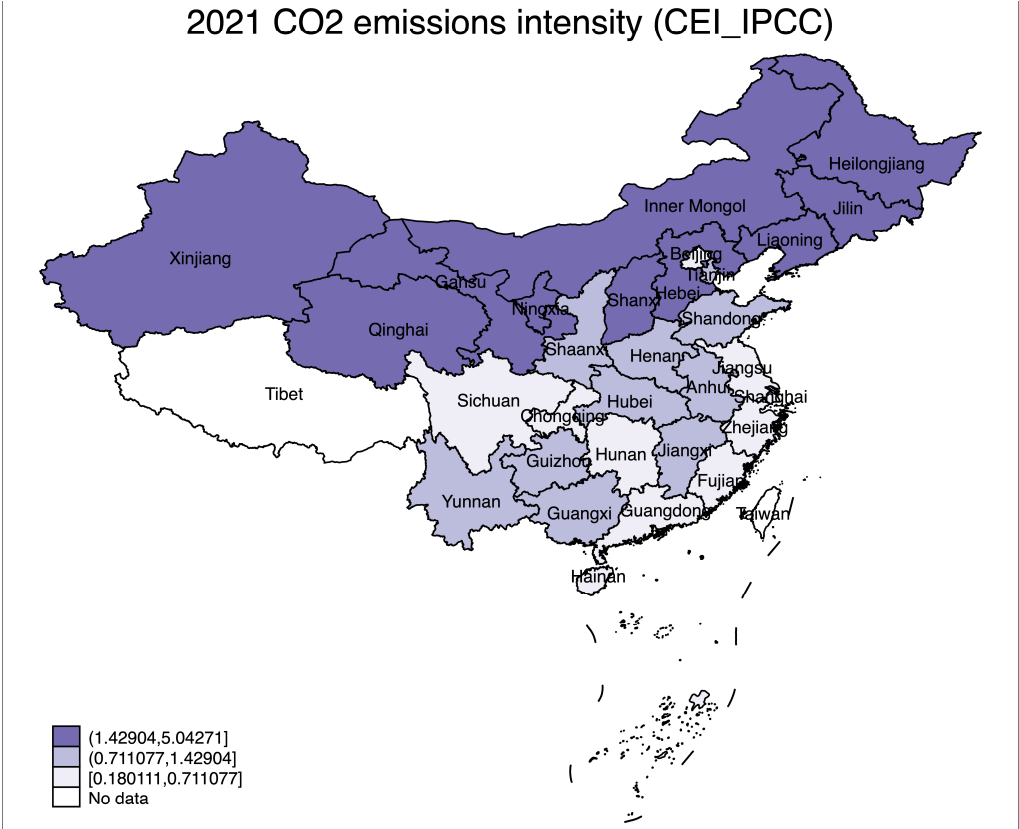


Figure A3. Spatial distribution of *CEI_IPCC* across 30 provinces in selected years (2005, 2010, 2015, 2020, 2021).

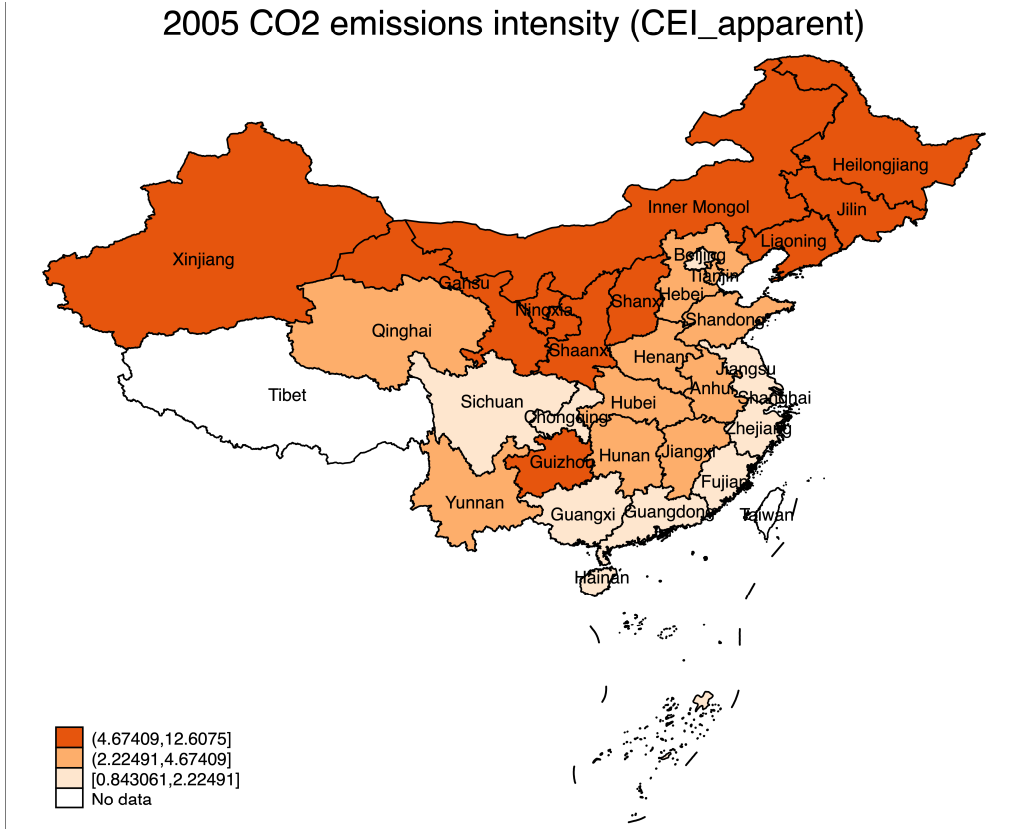


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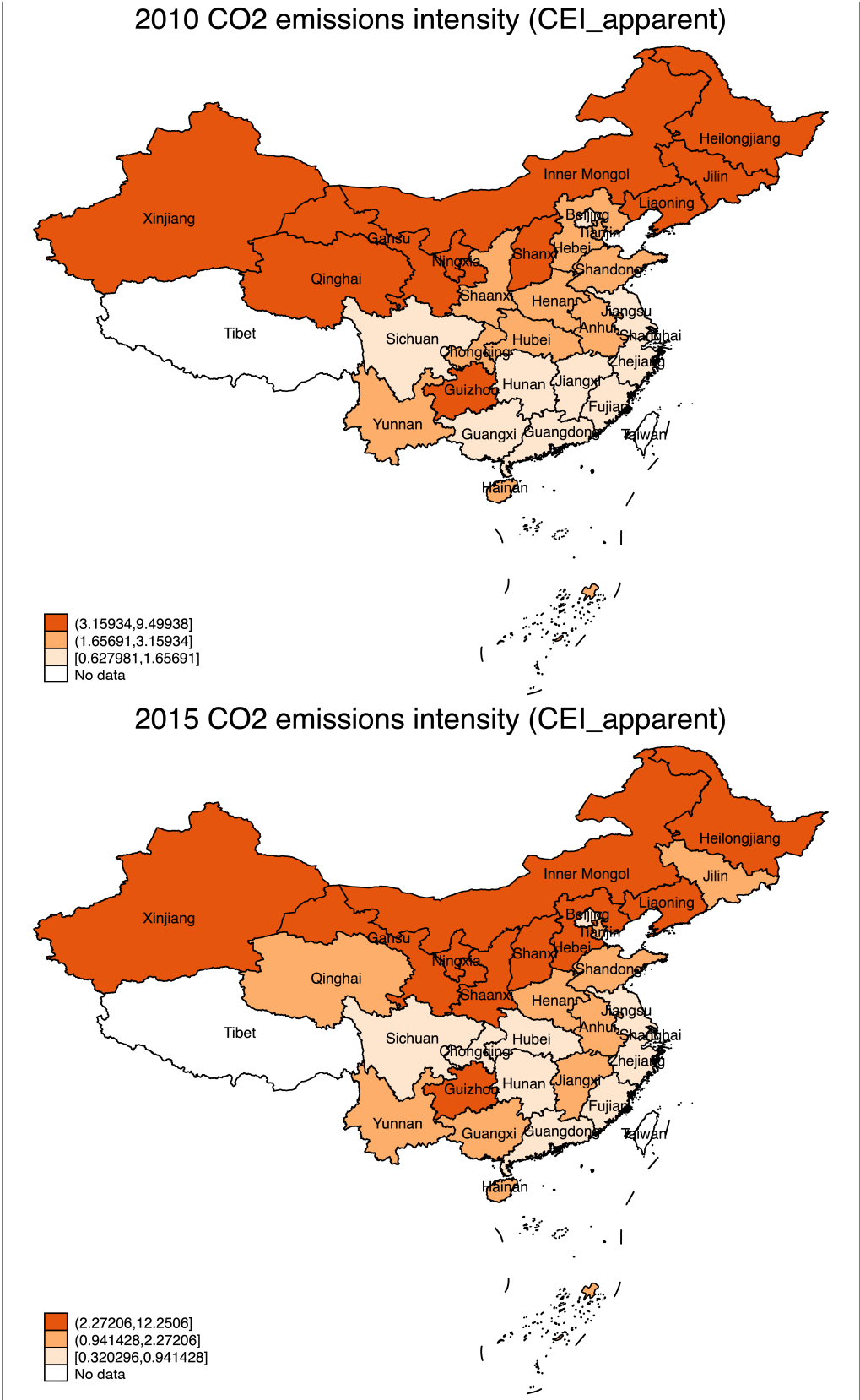


Figure A4. Cont.

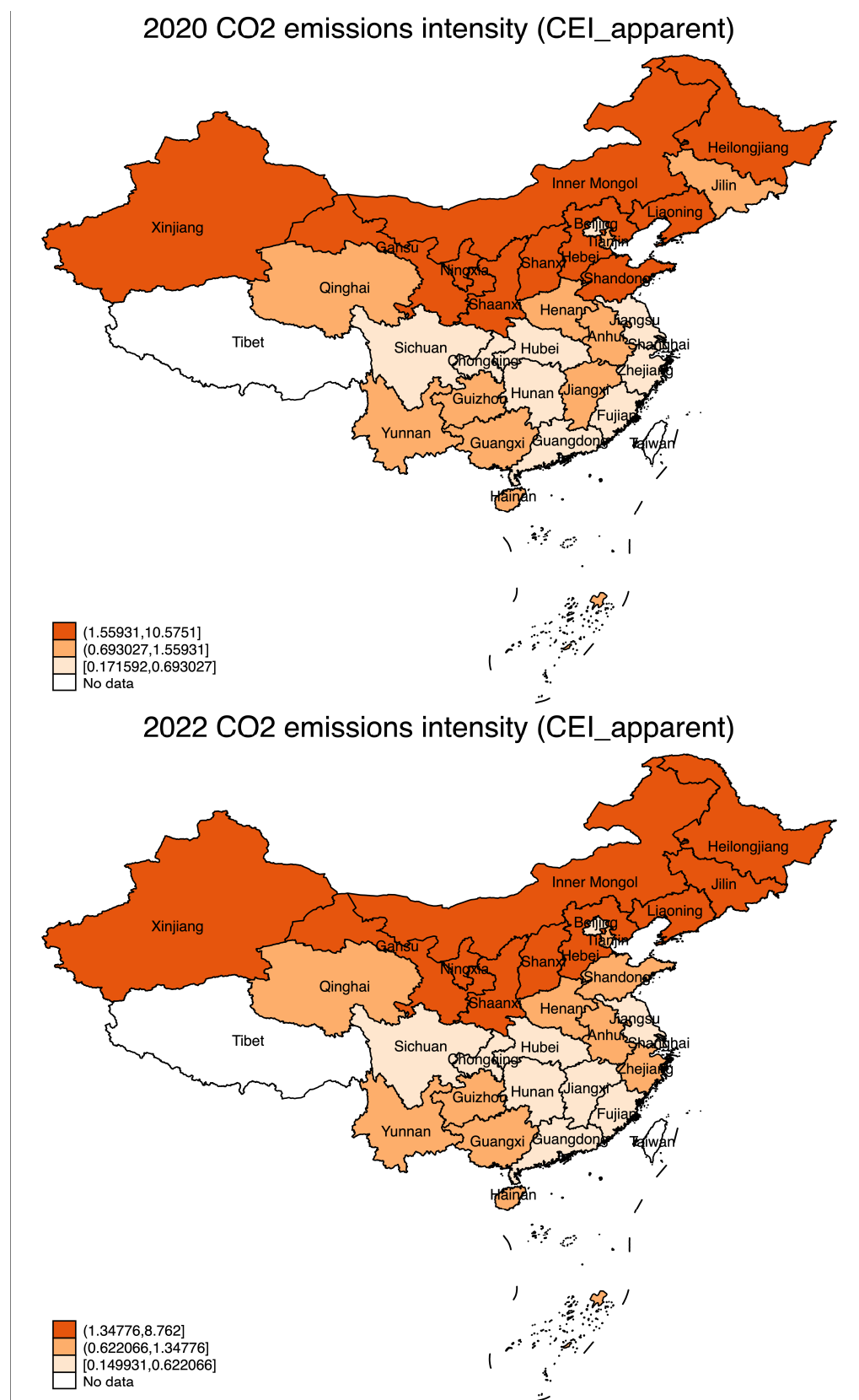


Figure A4. Spatial distribution of *CEI_apparent* across 30 provinces in selected years (2005, 2010, 2015, 2020, 2022).

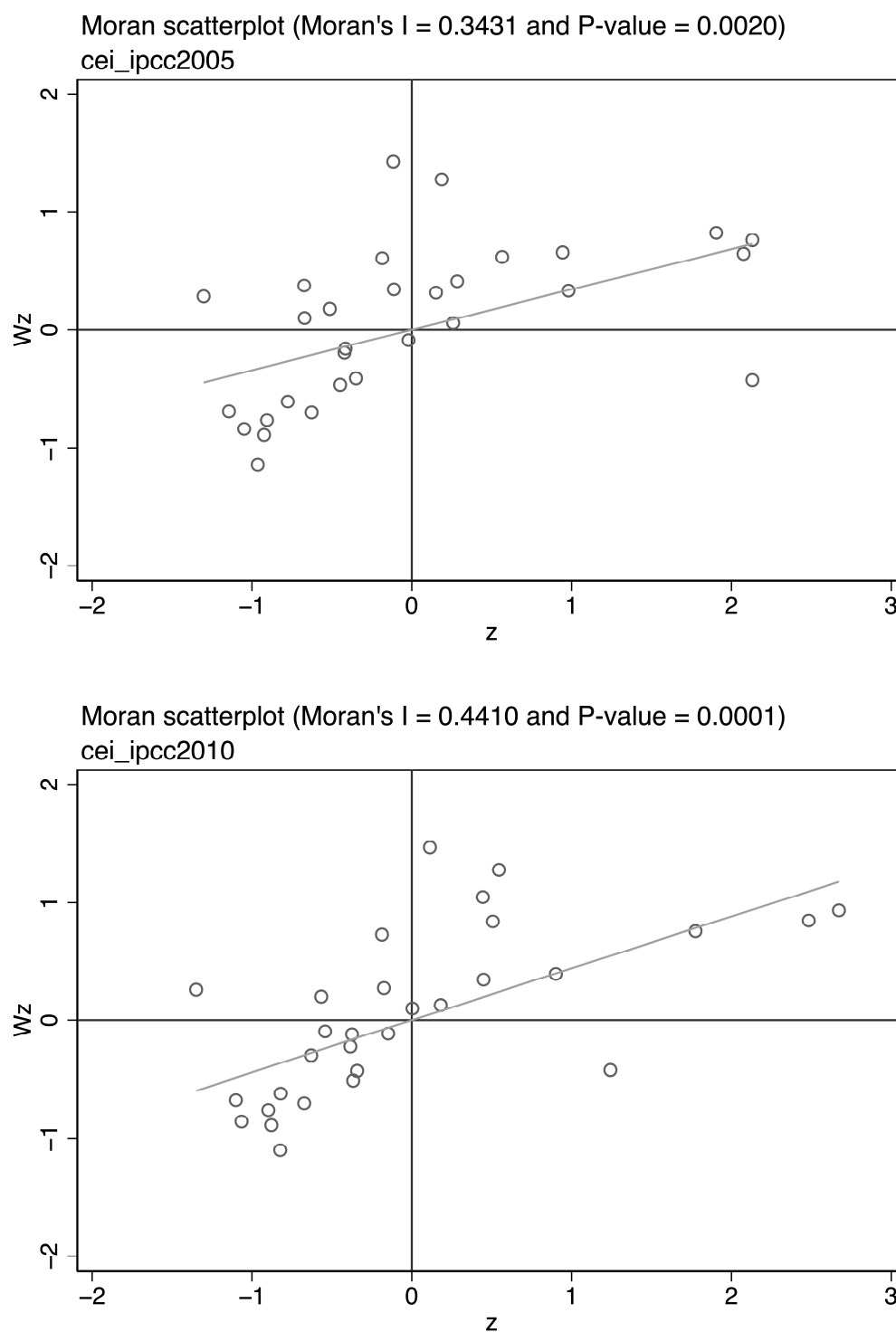


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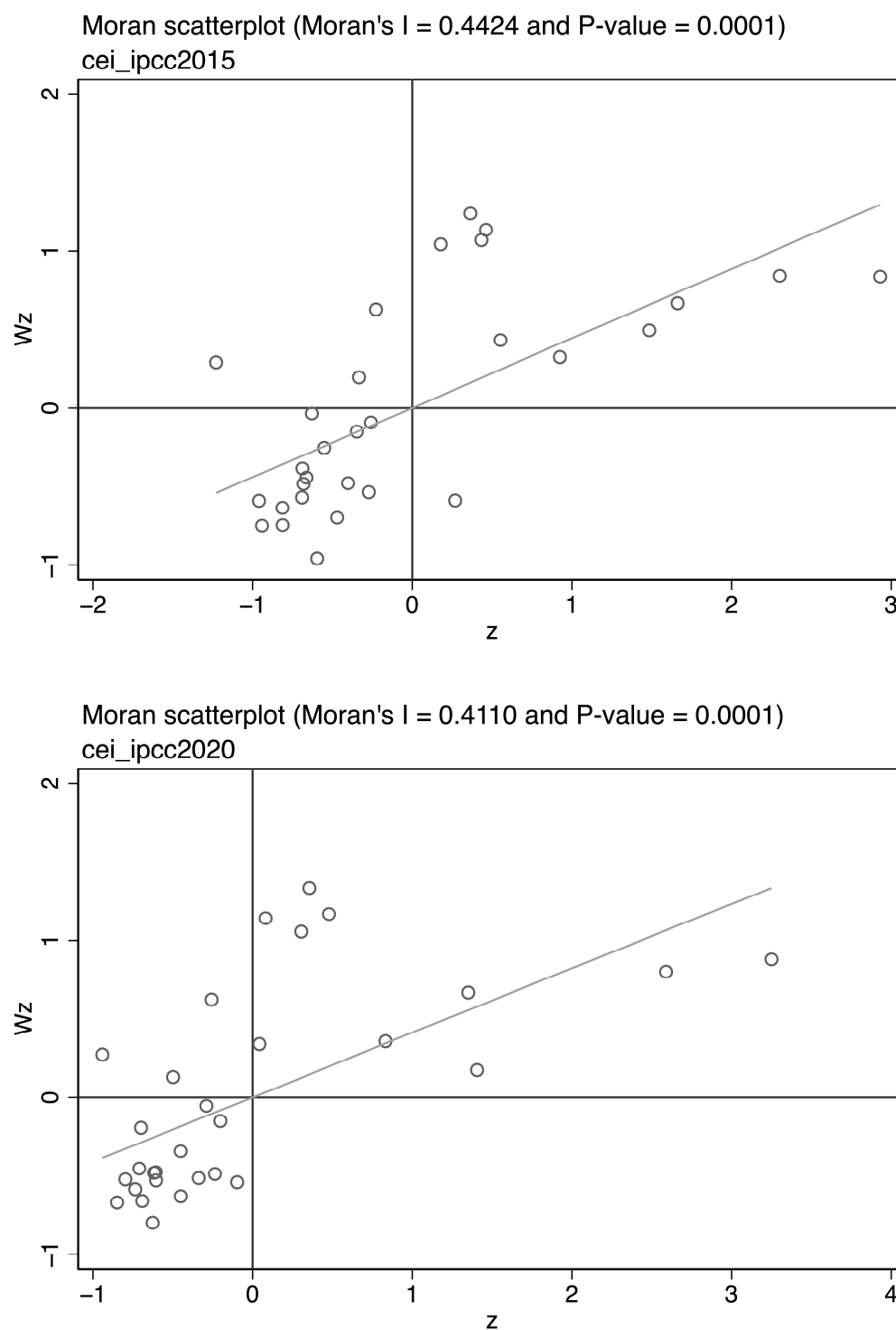


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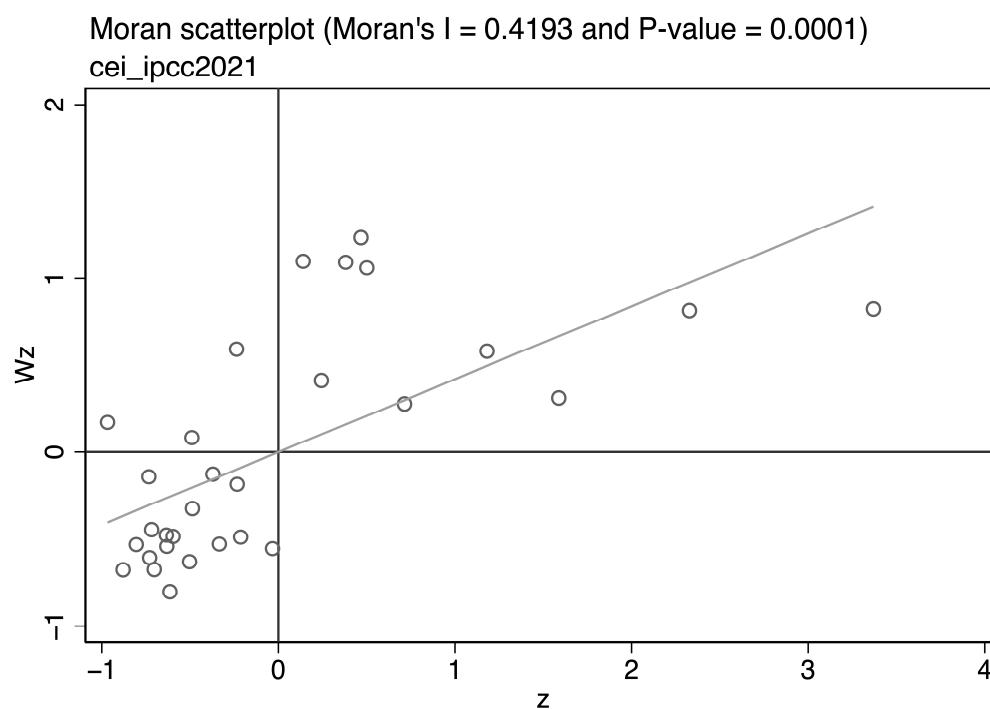


Figure A5. Moran's Index scatterplot of *CEI_IPCC* using provincial neighbor matrix weight ($W_{neighbor_{ij}^1}$) in selected years (2005, 2010, 2015, 2020, 2021). Note: The diagonal fitted line indicates the spatial association between provincial CEI and its spatial lag.

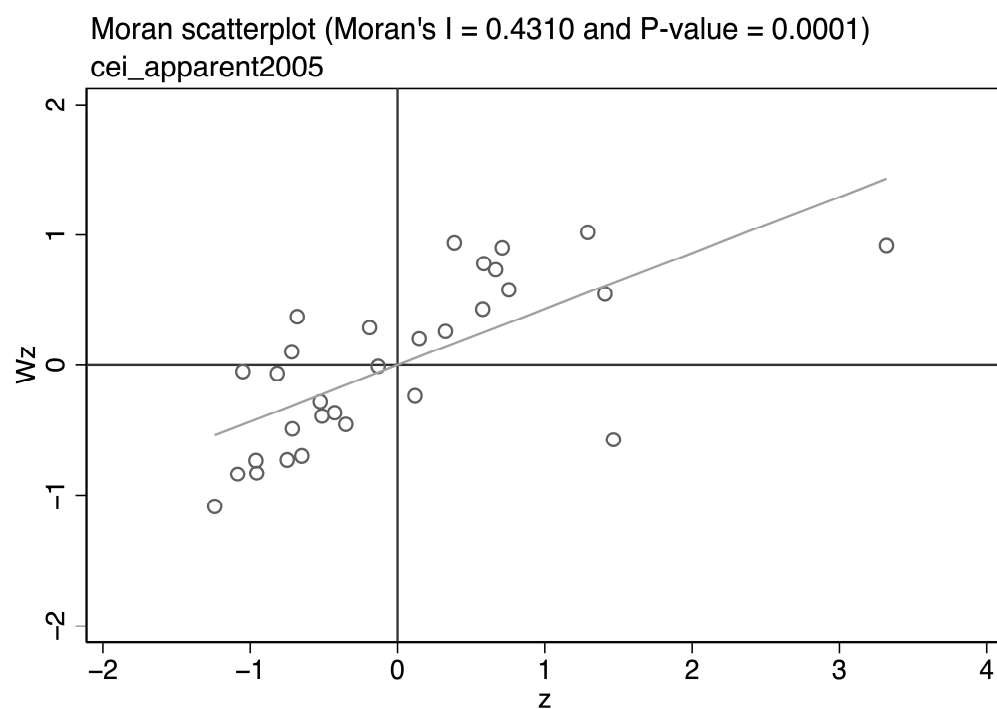


Figure A6. *Cont.*

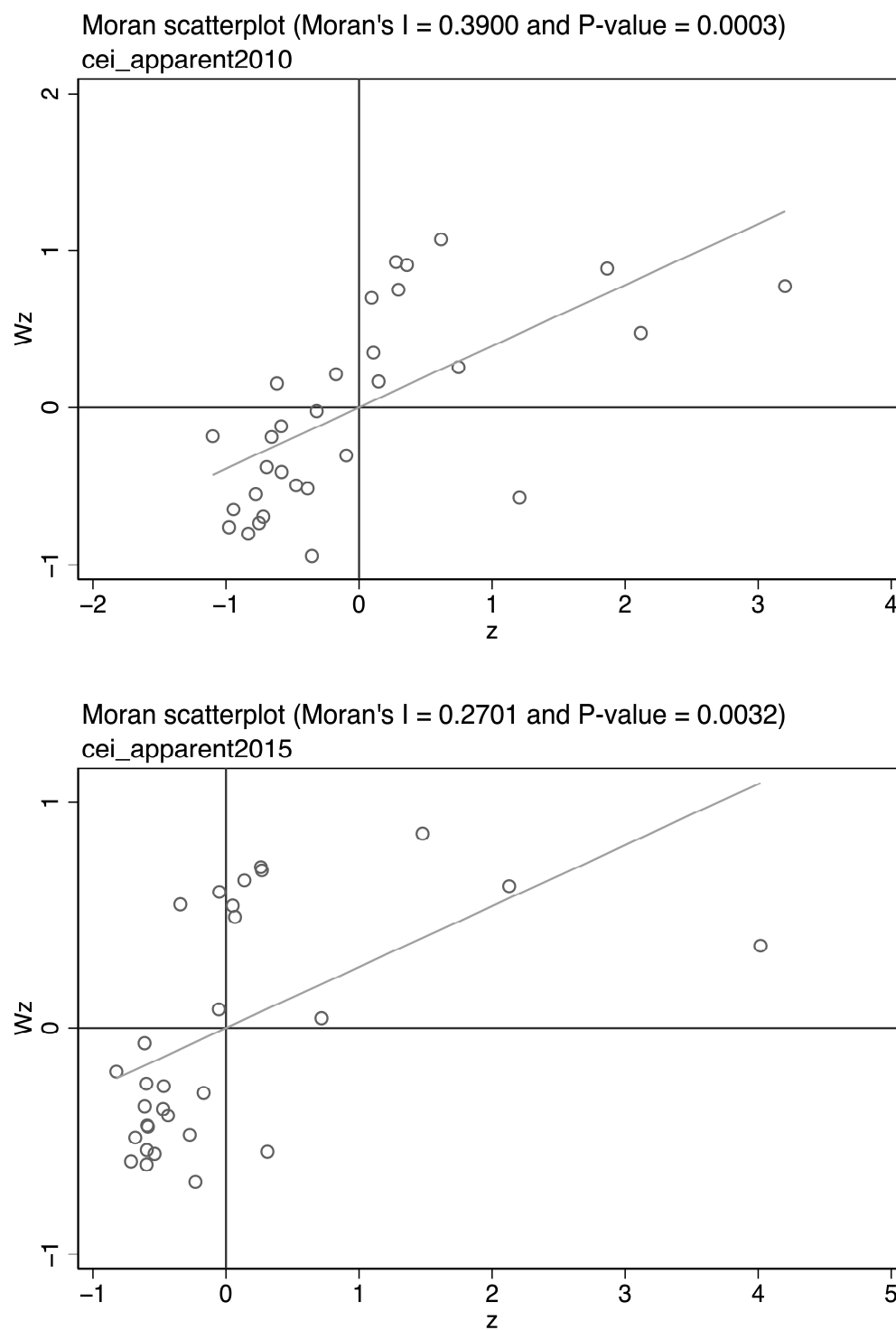


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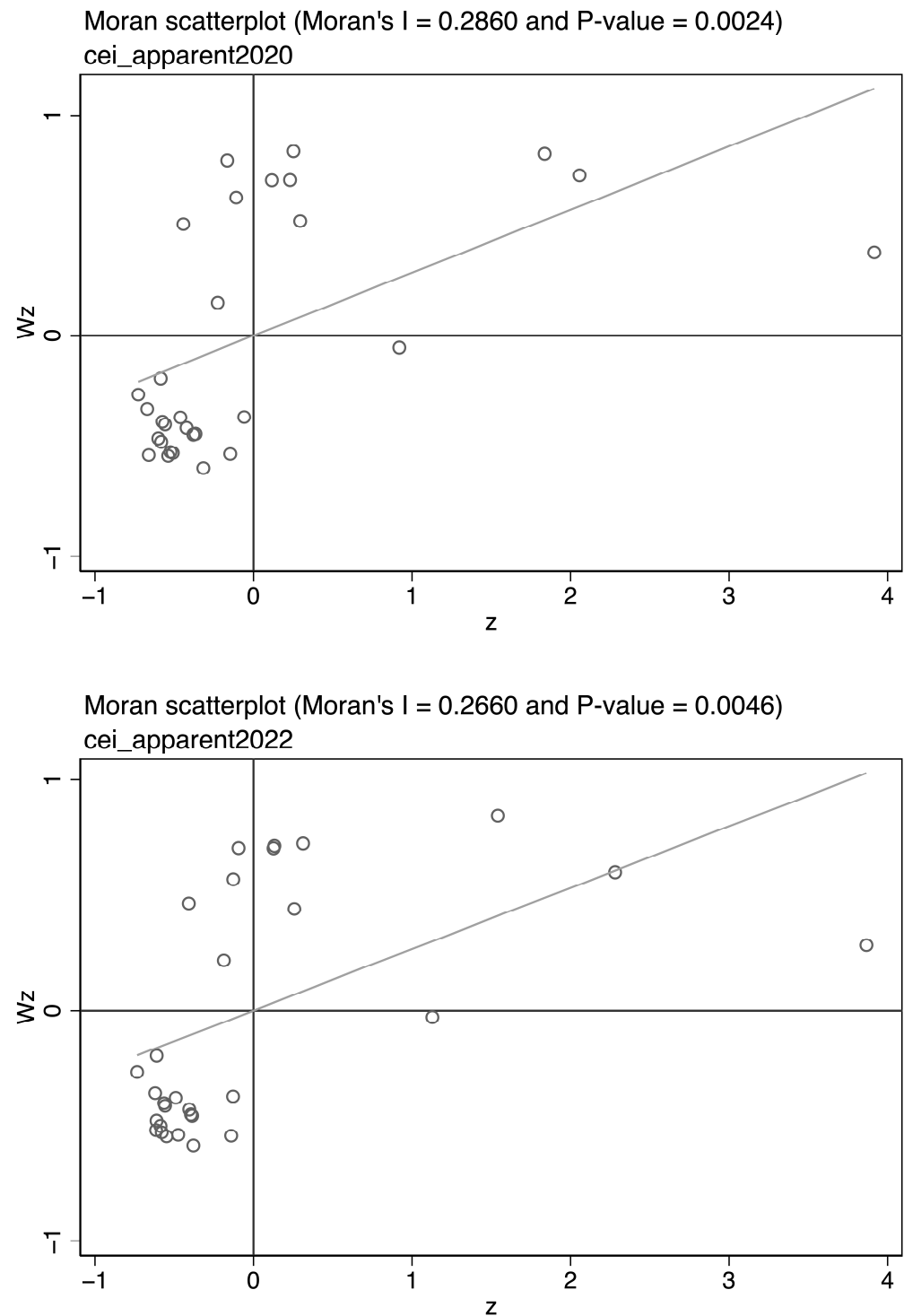


Figure A6. Moran's Index scatterplot of *CEI_apparent* using provincial neighbor matrix weight ($W_{neighbor_{ij}^1}$) in selected years (2005, 2010, 2015, 2020, 2022). Note: The diagonal fitted line indicates the spatial association between provincial CEI and its spatial lag.

Appendix C. Supplementary Model Construction: OLS

To establish a baseline relationship between REG and CEI, this study first estimates a conventional panel data model using ordinary least squares (OLS) [3,4]. The OLS model serves as a benchmark specification that captures the average effect of REG while controlling for key socio-economic variables and unobserved heterogeneity through fixed effects. The inclusion of province and year fixed effects helps control for time-invariant

regional characteristics and common shocks over time, respectively, thereby mitigating omitted variable bias. This specification provides an initial assessment of the direction and significance of the relationship between REG and CEI.

$$CEI_{it} = \alpha_0 + \alpha_1 REG_{it} + \alpha_2 Controls_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (A5)$$

where additional control variables, including foreign direct investment (*FDI*), technological innovation (*Tech*), and forest coverage (*Forest*), are not incorporated in the baseline model due to substantial missing observations in certain years. Instead, these variables are gradually introduced in the robustness checks to examine the sensitivity of the results.

Appendix D. Supplementary Empirical Analysis

Appendix D.1. Spatial Econometric Model Selection

Table A1. Test results of spatial econometric model selection using $W_distance_{ij}^2$.

Matrix: $W_distance_{ij}^2$ (Provincial Distance Weight Matrix)				
Panel A: <i>REG_share</i> and <i>CEI_EDGAR</i>				
LM test	Spatial error		Spatial lag	
	LM-error	76.069 ***	LM-lag	11.915 ***
LR test	Robust-LM-error	69.417 ***	Robust- LM-lag	5.263 **
	LR-error	78.210 ***	LR-lag	71.300 ***
Wald test	Wald-error	82.710 ***	Wald-lag	74.390 ***
Spatial Durbin's Model				
Fixed effect test	Both vs. Individual fixed	85.360 ***	Both vs. Time fixed	1077.100 ***
Panel B: <i>lnREG</i> and <i>CEI_EDGAR</i>				
LM test	Spatial error		Spatial lag	
	LM-error	79.581 ***	LM-lag	10.944 ***
LR test	Robust-LM-error	76.791 ***	Robust- LM-lag	8.154 ***
	LR-error	87.350 ***	LR-lag	77.130 ***
Wald test	Wald-error	93.670 ***	Wald-lag	80.060 ***
Spatial Durbin's Model				
Fixed effect test	Both vs. Individual fixed	81.880 ***	Both vs. Time fixed	1116.740 ***

Notes: The reported values correspond to test statistics from LM, LR, Wald and fixed effect tests, which follow a chi-square distribution. *** $p < 0.01$, ** $p < 0.05$. *REG_share* and *lnREG* denote REG. *CEI_EDGAR* denotes CEI. Panel A represents the results between *REG_share* and *CEI_EDGAR*. Panel B represents the results between *lnREG* and *CEI_EDGAR*.

Table A2. Test results of spatial econometric model selection using $W_PGDP_{ij}^3$.

Matrix: $W_PGDP_{ij}^3$ (Provincial Economic Weight Matrix)				
Panel A: <i>REG_share</i> and <i>CEI_EDGAR</i>				
LM test	Spatial error		Spatial lag	
	LM-error	1.269	LM-lag	2.778 *
LR test	Robust-LM-error	20.112 ***	Robust- LM-lag	21.621 ***
	LR-error	35.140 ***	LR-lag	33.600 ***
Wald test	Wald-error	36.230 ***	Wald-lag	34.480 ***
Spatial Durbin's Model				
Fixed effect test	Both vs. Individual fixed	62.900 ***	Both vs. Time fixed	1201.390 ***

Table A2. Cont.

Matrix: $W_PGDP_{ij}^3$ (Provincial Economic Weight Matrix)				
Panel B: $\ln REG$ and CEI_EDGAR				
LM test	Spatial error		Spatial lag	
	LM-error	1.914	LM-lag	2.430
LR test	Robust-LM-error	26.131 ***	Robust-LM-lag	26.648 ***
	LR-error	47.210 ***	LR-lag	42.530 ***
Wald test	Wald-error	49.370 ***	Wald-lag	43.770 ***
	Spatial Durbin's Model			
Fixed effect test	Both vs. Individual fixed	73.930 ***	Both vs. Time fixed	1217.410 ***

Notes: The reported values correspond to test statistics from LM, LR, Wald and fixed effect tests, which follow a chi-square distribution. *** $p < 0.01$, * $p < 0.1$. REG_share and $\ln REG$ denote REG. CEI_EDGAR denotes CEI. Panel A represents the results between REG_share and CEI_EDGAR . Panel B represents the results between $\ln REG$ and CEI_EDGAR .

Appendix D.2. OLS Benchmark Results

Table A3. OLS baseline results.

	(1) CEI_EDGAR	(2) CEI_IPCC	(3) $CEI_apparent$	(4) CEI_EDGAR
REG_share	−1.539 ** (0.649)	−2.337 *** (0.548)	−3.401 *** (0.970)	
$\ln REG$				−0.101 * (0.059)
$\ln PGDP$	−0.630 (0.500)	−0.568 (0.596)	−2.051 (1.575)	−0.773 * (0.439)
$Urban$	−5.034 *** (1.739)	−0.280 (2.704)	3.144 (6.020)	−5.877 *** (1.689)
$Indst$	0.417 (0.296)	0.344 (0.238)	0.430 (0.327)	0.373 (0.303)
$EnvirReg$	12.600 (23.680)	29.630 * (16.750)	−0.514 (42.130)	17.980 (24.810)
Constant	11.480 ** (5.334)	8.327 (6.330)	22.610 (14.280)	13.680 *** (4.876)
R^2	0.953	0.958	0.925	0.952
Observations	600	510	540	600
Province fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. REG_share and $\ln REG$ denote REG. CEI_EDGAR , CEI_IPCC and $CEI_apparent$ denote CEI.

Appendix D.3. Robustness Checks

Appendix D.3.1. SDM: Changing Sample Period

Table A4. SDM robustness check: using sample period from 2005 to 2023 ($W_neighbor_{ij}^1$).

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Parameter results (CEI_EDGAR)						
	Main (β)	WX (θ)	Spatial	Main (β)	WX (θ)	Spatial
REG_share	−0.951 *** (0.311)	−2.551 *** (0.525)				
$\ln REG$				−0.068 *** (0.023)	−0.113 *** (0.037)	
$\ln PGDP$	−0.674 *** (0.195)	1.508 *** (0.366)		−0.870 *** (0.206)	1.127 *** (0.396)	

Table A4. Cont.

<i>Urban</i>	−6.178 *** (0.876)	−8.026 *** (1.708)		−5.902 *** (0.886)	−7.089 *** (1.750)	
<i>Indst</i>	0.399 *** (0.087)	0.200 (0.178)		0.429 *** (0.088)	0.418 ** (0.182)	
<i>EnvirReg</i>	2.351 (8.124)	−9.469 (16.040)		12.930 (8.239)	40.230 ** (15.830)	
Rho (ρ)			−0.223 *** (0.059)			−0.155 *** (0.059)
R ²	0.333	0.333	0.333	0.408	0.408	0.408
Observations	570	570	570	570	570	570
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Direct, indirect and total effect (<i>CEI_EDGAR</i>)						
	Direct	Indirect	Total	Direct	Indirect	Total
<i>REG_share</i>	−0.824 ** (0.332)	−2.009 *** (0.476)	−2.833 *** (0.361)			
<i>lnREG</i>				−0.064 *** (0.024)	−0.091 *** (0.035)	−0.154 *** (0.028)
<i>lnPGDP</i>	−0.764 *** (0.190)	1.440 *** (0.322)	0.676 ** (0.313)	−0.923 *** (0.199)	1.145 *** (0.359)	0.223 (0.377)
<i>Urban</i>	−5.755 *** (0.857)	−5.819 *** (1.399)	−11.570 *** (1.369)	−5.591 *** (0.856)	−5.620 *** (1.491)	−11.210 *** (1.512)
<i>Indst</i>	0.396 *** (0.087)	0.106 (0.143)	0.502 *** (0.173)	0.419 *** (0.087)	0.326 ** (0.152)	0.745 *** (0.182)
<i>EnvirReg</i>	2.907 (8.036)	−7.976 (14.190)	−5.069 (14.360)	11.620 (8.059)	34.640 ** (14.280)	46.260 *** (14.520)
R ²	0.333	0.333	0.333	0.408	0.408	0.408
Observations	570	570	570	570	570	570
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$. *REG_share* and *lnREG* denote REG. *CEI_EDGAR* denotes CEI. Panel A shows the analysis of SDM results. Panel B shows the decomposition of SDM effects, including direct, indirect and total effect. The same arrangements apply to the following tables.

Table A5. SDM robustness check: using sample period from 2005 to 2019 ($W_neighbor_{ij}^1$).

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Parameter results (<i>CEI_IPCC</i>)						
	Main (β)	WX (θ)	Spatial	Main (β)	WX (θ)	Spatial
<i>REG_share</i>	−1.870 *** (0.384)	−1.772 *** (0.657)				
<i>lnREG</i>				−0.017 (0.027)	−0.143 *** (0.045)	
<i>lnPGDP</i>	−0.456 ** (0.220)	0.468 (0.426)		−0.623 *** (0.236)	−0.097 (0.466)	
<i>Urban</i>	0.491 (1.120)	−5.693 *** (2.127)		−0.068 (1.181)	−6.048 *** (2.227)	
<i>Indst</i>	0.401 *** (0.118)	−0.134 (0.231)		0.353 *** (0.121)	−0.247 (0.245)	
<i>EnvirReg</i>	25.180 *** (8.420)	−11.560 (17.190)		29.520 *** (8.838)	29.740 (18.68)	
Rho (ρ)			−0.069 (0.070)			0.055 (0.067)
R ²	0.188	0.188	0.188	0.343	0.343	0.343
Observations	450	450	450	450	450	450
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes

Table A5. Cont.

	Panel B: Direct, indirect and total effect (<i>CEI_IPCC</i>)					
	Direct	Indirect	Total	Direct	Indirect	Total
<i>REG_share</i>	−1.831 *** (0.395)	−1.541 ** (0.615)	−3.371 *** (0.519)			
<i>lnREG</i>				−0.017 (0.028)	−0.149 *** (0.045)	−0.166 *** (0.044)
<i>lnPGDP</i>	−0.473 ** (0.213)	0.475 (0.407)	0.002 (0.423)	−0.632 *** (0.228)	−0.126 (0.485)	−0.759 (0.540)
<i>Urban</i>	0.699 (1.069)	−5.551 *** (1.915)	−4.852 ** (2.047)	−0.029 (1.124)	−6.428 *** (2.201)	−6.457 *** (2.454)
<i>Indst</i>	0.407 *** (0.118)	−0.142 (0.213)	0.265 (0.271)	0.355 *** (0.123)	−0.225 (0.254)	0.130 (0.322)
<i>EnvirReg</i>	25.500 *** (8.181)	−11.930 (16.320)	13.560 (17.660)	29.990 *** (8.525)	32.990 * (19.100)	62.980 *** (21.430)
R ²	0.188	0.188	0.188	0.343	0.343	0.343
Observations	450	450	450	450	450	450
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *REG_share* and *lnREG* denote REG. *CEI_IPCC* denotes CEI.

Appendix D.3.2. SDM: Changing Measurements of Y

Table A6. SDM robustness check: using *CEI_IPCC* as Y ($W_{neighbor_{ij}}^1$).

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Parameter results (<i>CEI_IPCC</i>)					
	Main (β)	WX (θ)	Spatial	Main (β)	WX (θ)	Spatial
<i>REG_share</i>	−2.032 *** (0.340)	−1.440 ** (0.594)				
<i>lnREG</i>				−0.0133 (0.025)	−0.131 *** (0.041)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Rho (ρ)			−0.076 (0.066)			0.047 (0.063)
R ²	0.313	0.313	0.313	0.357	0.357	0.357
Observations	510	510	510	510	510	510
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B: Direct, indirect and total effect (<i>CEI_IPCC</i>)					
	Direct	Indirect	Total	Direct	Indirect	Total
<i>REG_share</i>	−1.998 *** (0.352)	−1.194 ** (0.553)	−3.192 *** (0.465)			
<i>lnREG</i>				−0.014 (0.025)	−0.135 *** (0.041)	−0.149 *** (0.038)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.313	0.313	0.313	0.357	0.357	0.357
Observations	510	510	510	510	510	510
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$. *REG_share* and *lnREG* denote REG. *CEI_IPCC* denotes CEI.

Table A7. SDM robustness check: using $CEI_apparent$ as Y ($W_neighbor_{ij}^1$).

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Parameter results ($CEI_apparent$)						
	Main (β)	WX (θ)	Spatial	Main (β)	WX (θ)	Spatial
REG_share	−2.681 *** (0.643)	−2.072 * (1.127)				
$lnREG$				−0.078 * (0.047)	−0.151 ** (0.076)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Rho (ρ)			−0.065 (0.076)			0.010 (0.073)
R ²	0.181	0.181	0.181	0.180	0.180	0.180
Observations	540	540	540	540	540	540
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Direct, indirect and total effect ($CEI_apparent$)						
	Direct	Indirect	Total	Direct	Indirect	Total
REG_share	−2.630 *** (0.668)	−1.769 * (1.056)	−4.399 *** (0.895)			
$lnREG$				−0.077 (0.048)	−0.150 ** (0.075)	−0.227 *** (0.068)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.181	0.181	0.181	0.180	0.180	0.180
Observations	540	540	540	540	540	540
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. REG_share and $lnREG$ denote REG. $CEI_apparent$ denotes CEI.

Appendix D.3.3. SDM: Changing Fixed Effect

Table A8. SDM robustness check: adding region $\times$ year fixed effect ($W_neighbor_{ij}^1$).

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Parameter results (CEI_EDGAR)						
	Main (β)	WX (θ)	Spatial	Main (β)	WX (θ)	Spatial
REG_share	−1.218 *** (0.255)	−2.364 *** (0.517)				
$lnREG$				−0.080 *** (0.020)	−0.122 *** (0.033)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Rho (ρ)			−0.510 *** (0.061)			−0.532 *** (0.062)
R ²	0.308	0.308	0.308	0.306	0.306	0.306
Observations	600	600	600	600	600	600
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Region $\times$ Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Direct, indirect and total effect (CEI_EDGAR)						
	Direct	Indirect	Total	Direct	Indirect	Total
REG_share	−1.014 *** (0.300)	−1.350 *** (0.454)	−2.364 *** (0.329)			
$lnREG$				−0.069 *** (0.024)	−0.0628 ** (0.031)	−0.132 *** (0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.308	0.308	0.308	0.306	0.306	0.306
Observations	600	600	600	600	600	600
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Region $\times$ Year fixed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$. REG_share and $lnREG$ denote REG. CEI_EDGAR denotes CEI.

Appendix D.3.4. SDM: Changing Spatial Matrix

Table A9. SDM robustness check: changing spatial matrix using $W_{distance^2_{ij}}$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Parameter results (<i>CEI_EDGAR</i>)					
	Main (β)	WX (θ)	Spatial	Main (β)	WX (θ)	Spatial
<i>REG_share</i>	−0.892 *** (0.264)	−3.822 ** (1.544)				
<i>lnREG</i>				−0.093 *** (0.0194)	−0.154 (0.108)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Rho (ρ)			0.209 (0.132)			0.245 * (0.127)
R ²	0.019	0.019	0.019	0.203	0.203	0.203
Observations	600	600	600	600	600	600
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B: Direct, indirect and total effect (<i>CEI_EDGAR</i>)					
	Direct	Indirect	Total	Direct	Indirect	Total
<i>REG_share</i>	−0.937 *** (0.265)	−5.021 ** (2.068)	−5.958 *** (2.046)			
<i>lnREG</i>				−0.095 *** (0.020)	−0.230 (0.147)	−0.324 ** (0.149)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.019	0.019	0.019	0.203	0.203	0.203
Observations	600	600	600	600	600	600
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *REG_share* and *lnREG* denote REG. *CEI_EDGAR* denotes CEI.

Table A10. SDM robustness check: changing spatial matrix using $W_{PGDP^3_{ij}}$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Parameter results (<i>CEI_EDGAR</i>)					
	Main (β)	WX (θ)	Spatial	Main (β)	WX (θ)	Spatial
<i>REG_share</i>	−1.645 *** (0.265)	−1.893 *** (0.558)				
<i>lnREG</i>				−0.107 *** (0.019)	−0.146 ** (0.064)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Rho (ρ)			−0.066 (0.076)			−0.064 (0.077)
R ²	0.431	0.431	0.431	0.426	0.426	0.426
Observations	600	600	600	600	600	600
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B: Direct, indirect and total effect (<i>CEI_EDGAR</i>)					
	Direct	Indirect	Total	Direct	Indirect	Total
<i>REG_share</i>	−1.614 *** (0.266)	−1.673 *** (0.536)	−3.287 *** (0.655)			
<i>lnREG</i>				−0.104 *** (0.020)	−0.129 ** (0.059)	−0.234 *** (0.058)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.431	0.431	0.431	0.426	0.426	0.426
Observations	600	600	600	600	600	600
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$. *REG_share* and *lnREG* denote REG. *CEI_EDGAR* denotes CEI.

Appendix D.3.5. SDM: Changing Regression Model

Table A11. SDM robustness check: using dynamic SDM ($W_neighbor_{ij}^1$).

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Parameter results (<i>CEI_EDGAR</i>)					
	Main (β)	WX (θ)	Spatial	Main (β)	WX (θ)	Spatial
<i>L.CEI_EDGAR</i>	0.843 *** (0.016)	−0.087 (0.062)		0.842 *** (0.016)	−0.082 (0.061)	
<i>REG_share</i>	−0.257 ** (0.113)	−0.055 (0.198)				
<i>lnREG</i>				−0.0131 (0.008)	−0.0224 (0.014)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Rho (ρ)			0.029 (0.061)			0.017 (0.062)
R ²	0.984	0.984	0.984	0.981	0.981	0.981
Observations	570	570	570	570	570	570
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B: Direct, indirect and total effect (<i>CEI_EDGAR</i>)					
	Direct	Indirect	Total	Direct	Indirect	Total
<i>L.CEI_EDGAR</i>	0.843 *** (0.017)	−0.067 * (0.035)	0.777 *** (0.0425)	0.842 *** (0.017)	−0.071 ** (0.033)	0.771 *** (0.040)
<i>REG_share</i>	−0.262 ** (0.109)	−0.0638 (0.198)	−0.325 * (0.185)			
<i>lnREG</i>				−0.014 * (0.008)	−0.023 * (0.014)	−0.036 *** (0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.984	0.984	0.984	0.981	0.981	0.981
Observations	570	570	570	570	570	570
Number of provinces	30	30	30	30	30	30
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *REG_share* and *lnREG* denote REG. *CEI_EDGAR* denotes CEI.

Appendix D.3.6. OLS: Adding Control Variables

Table A12. OLS robustness check: adding more control variables.

	(1) <i>CEI_EDGAR</i>	(2) <i>CEI_IPCC</i>	(3) <i>CEI_EDGAR</i>	(4) <i>CEI_IPCC</i>	(5) <i>CEI_EDGAR</i>	(6) <i>CEI_IPCC</i>
<i>REG_share</i>	−1.752 ** (0.710)	−2.213 *** (0.558)	−1.112 ** (0.414)	−1.672 *** (0.393)	−1.112 ** (0.415)	−1.642 *** (0.403)
<i>lnPGDP</i>	−0.572 (0.564)	−0.579 (0.624)	−0.525 (0.378)	−0.872 (0.537)	−0.541 (0.390)	−0.501 (0.354)
<i>Urban</i>	−4.113 ** (1.617)	−0.881 (2.493)	−5.054 *** (1.700)	−2.825 (2.257)	−5.028 *** (1.637)	−3.448 (2.358)
<i>Indst</i>	0.532 * (0.302)	0.293 (0.230)	0.479 ** (0.191)	0.290 (0.179)	0.474 ** (0.197)	0.390 ** (0.165)
<i>EnvirReg</i>	9.463 (23.960)	28.120 (17.010)	11.410 (11.220)	2.350 (15.59)	11.600 (10.850)	−2.239 (14.560)
<i>FDI</i>	−0.924 (2.903)	−0.726 (2.313)	−4.906 ** (2.105)	−0.124 (1.958)	−4.911 ** (2.127)	−0.081 (1.920)
<i>Tech</i>			47.700 ** (19.870)	24.860 (19.010)	47.690 ** (19.840)	25.740 (17.280)
<i>Forest</i>					0.261 (2.357)	−5.342 * (2.720)
Constant	10.300 (6.116)	8.860 (6.802)	9.697 ** (3.905)	12.690 * (6.399)	9.779 ** (3.935)	10.730 ** (4.635)
R ²	0.953	0.958	0.976	0.980	0.976	0.981
Observations	559	492	443	376	443	376
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *REG_share* and *lnREG* denote REG. *CEI_EDGAR* and *CEI_IPCC* denote CEI.

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