

Economic, social, environmental, and institutional factors shaping onshore wind LCOE in Europe: Evidence from spatial panel models

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HIGHLIGHTS

- Economic and institutional performance are associated with lower onshore wind LCOE.
- Human development is associated with higher onshore wind LCOE.
- Higher emission intensity is associated with higher onshore wind LCOE.
- Spatial spillovers matter for economic performance, emissions, and institutions.
- Cost-reduction policies should account for domestic impacts and spatial spillovers.

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ABSTRACT

We investigate how macro-level factors—economic, social, environmental, and institutional—shape the levelized cost of electricity (LCOE) for onshore wind energy in Europe over time, while accounting for spatial dependence. Using a balanced annual panel of 10 OECD European countries from 2011 to 2023, we estimate a Spatial Durbin Model with two-way fixed effects, which receives the strongest overall support among the non-spatial and spatial models considered. By decomposing total impacts into direct and indirect impacts, we find that macro-level factors are associated with LCOE through domestic and spatial spillover channels. Stronger economic and institutional performance is associated with lower LCOE through both channels, with spatial spillovers larger than the corresponding direct impacts. Higher emission intensity is associated with higher LCOE through both channels, whereas higher human development is associated with higher LCOE primarily through the domestic channel. Among the control variables, the association with LCOE is negative for cumulative onshore wind electricity generation and cumulative wind energy patents, but positive for renewable electricity generation share. Overall, our findings highlight cross-country spatial dependence and suggest that onshore wind energy cost-reduction policies in Europe should consider regional coordination rather than focusing exclusively on national conditions.

1. Introduction

The global transition to renewable energy has increased the need for cost-effective energy generation strategies (Elkadeem et al., 2025), especially in the wind energy sector (Weinand et al., 2022). This transition is primarily driven by global efforts to mitigate climate change, secure a sustainable energy supply, and ensure energy security (Johnston et al., 2024; Watson et al., 2019). Over the past two decades, these drivers have influenced the wind energy sector at the micro-level through technical, policy, and project-related channels. Studies linking the global energy transition to economic, social, environmental, and institutional dimensions (Black et al., 2024; Le Treut et al., 2021; IPCC, 2023;

Kruyt et al., 2009; Lu et al., 2020) show that these drivers have also changed the broader macro-level conditions of the wind energy sector. As cost-effectiveness becomes increasingly important, these evolving macro-level conditions are likely to feed into the wind energy sector's cost structure (e.g., planning, financing, and operating costs), thereby affecting energy generation costs. Therefore, examining these cost implications is particularly important for onshore wind, which remains the most cost-effective source of newly commissioned renewable electricity (IRENA, 2026b).

The industry-standard measure for comparing the costs of different energy sources is the levelized cost of electricity (LCOE), defined

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Nomenclature**Abbreviations**

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BMC	Bayesian Model Comparison
DGP	Data Generating Process
EPSP	European Petroleum Survey Group
FE	Fixed Effects
GDP	Gross Domestic Product per capita
GHG	Greenhouse Gas Emissions per capita
GNS	General Nesting Spatial Model
GRI	Governance Readiness Index
HDI	Human Development Index
IRENA	International Renewable Energy Agency
LCOE	Levelized Cost of Electricity
LL	Log-likelihood
LM	Lagrange Multiplier
OECD	Organisation for Economic Co-operation and Development
QML	Quasi-Maximum Likelihood
RE	Random Effects
REGS	Renewable Electricity Generation Share

SAC	Spatial Autoregressive Combined Model
SAR	Spatial Autoregressive Model
SDM	Spatial Durbin Error Model
SDM	Spatial Durbin Model
SEM	Spatial Error Model
SLX	Spatially Lagged X Model
WEGC	Cumulative Onshore Wind Electricity Generation
WEPC	Cumulative Wind Energy Patents
WGI	Worldwide Governance Indicators

Symbols

β	Coefficient vector
λ	Spatial autocorrelation parameter
ρ	Spatial autoregressive parameter
θ	Spatial spillover parameter vector
C	Contiguity matrix
K	Number of explanatory variables
N	Number of cross-sectional units
T	Number of time periods
W	Spatial weight matrix
X_t	Explanatory variable matrix
Y_t	Dependent variable vector

as the average cost of generating electricity in USD per kilowatt-hour (USD/kWh) over a technology's lifetime. It also enables consistent cost comparisons across countries and technologies with varying cost structures and operational lifetimes (Béres et al., 2024). According to a recent report by the International Renewable Energy Agency (IRENA), onshore wind is one of the most cost-effective sources of renewable energy in the world, with a weighted average LCOE of USD 0.054/kWh in Europe and USD 0.033/kWh globally (IRENA, 2026b). Across regions and countries, the weighted averages range from USD 0.027/kWh in China to USD 0.083/kWh in Other Asia, which comprises all Asian countries except China and India (IRENA, 2026b).

Prior research typically examines how micro-level and project-level factors influence onshore wind LCOE; however, comparatively little is known about the relationship between macro-level factors and LCOE across countries and over time, particularly when spatial proximity is considered. Accounting for spatial proximity, and hence spatial interactions, is crucial because Tobler's First Law of Geography states that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). For instance, ignoring cross-country spatial interactions in onshore wind LCOE may be misleading when spillovers occur via the cross-border diffusion of technology, finance, labor costs, and policy, as well as through shared energy infrastructure (Lohr et al., 2024; McKenna et al., 2022). In integrated regions such as Europe, these mechanisms create spatial dependence that may influence onshore wind LCOE.

This research addresses these gaps by examining how macro-level economic, social, environmental, and institutional factors are associated with onshore wind LCOE across countries and over time. The study makes three main contributions. First, while the existing LCOE literature primarily focuses on technical, policy, sector-specific, and project-level determinants, we provide cross-country evidence on the relationship between a broader set of macro-level factors and onshore wind LCOE within a unified empirical framework. Second, we explicitly account for the spatial dimension of these relationships. Rather than treating countries as independent units, we distinguish between domestic impacts and cross-border spatial spillovers, thereby examining whether macro-level factors in one country are associated with onshore wind costs in neighboring countries. Third, this distinction provides an economic perspective on the determinants of onshore wind costs by showing whether the relationships between macro-level factors and

LCOE operate primarily within national borders or through spatially connected economies. Accordingly, the contribution of the study is empirical and substantive rather than methodological: established spatial panel econometric methods are used to identify and interpret economically relevant domestic and cross-border relationships that conventional non-spatial approaches do not explicitly capture (LeSage and Pace, 2009; Elhorst, 2014).

The research question is highly relevant to policymakers. As noted by IRENA (2026b), countries experience significant cost differences in the onshore wind energy sector. In response, many governments pursue regional cooperation to share infrastructure, exchange knowledge, and align policies, all aimed at reducing costs. Therefore, gaining a clear understanding of how macro-level factors are associated with onshore wind LCOE through domestic impacts and cross-border spatial spillovers can help policymakers not only set the right priorities for potential reforms but also anticipate the effects of domestic policies both within and across countries.

The remainder of the paper is organized as follows. In Section 2, we review the existing literature on the relationship between macro-level factors and onshore wind LCOE, with particular emphasis on the empirical studies that have shaped our understanding of this relationship. Section 3 presents and describes the data sources and variables used in the study. Section 4 details the spatial panel econometric techniques employed, including the model specifications and estimation strategies. Section 5 reports the primary estimation results and provides a comprehensive discussion. Finally, Section 6 summarizes the main findings, provides policy implications, discusses limitations, and offers recommendations for future research.

2. Literature review

Across varying energy technologies, existing research on the determinants of LCOE primarily focuses on micro-level factors (e.g., technical, policy, and sector-specific) and project-level factors (e.g., capital, operation and maintenance, and system integration costs). Many studies of wind energy generally adopt the same focus in the context of the ongoing energy transition (Johnston et al., 2022; Klie and Madlener, 2024; Langer et al., 2023; Li et al., 2024; Patel et al., 2025; Ryberg et al., 2019; Santhakumar et al., 2023; Tumse et al., 2024). In contrast, evidence on whether and how macro-level factors shape onshore wind

LCOE is scarce. While a number of renewable energy studies document the impact of macro-level factors on deployment, generation, and consumption, these findings are rarely mapped directly to onshore wind LCOE within a single spatial econometric framework. To address this gap, we examine how macro-level economic, social, environmental, and institutional factors shape onshore wind LCOE across countries and over time, using a spatial panel model that allows for both domestic impacts and cross-border spatial spillovers. Accordingly, the literature review is organized around these four categories of macro-level factors.

Apart from studies examining factor-specific relationships, one study reports spatial spillovers in renewable energy technologies while examining multiple macro-level factors. Applying a spatial econometric model to 60 countries (1995–2018), [Nan et al. \(2023\)](#) provide evidence of spatial dependence in renewable energy consumption across countries and reveal significant direct, indirect, and total impacts of globalization on this consumption. While this evidence pertains to consumption rather than cost, it highlights the importance of economic, political, and social cross-border spillovers in renewable energy markets, thereby motivating our study.

2.1. Economic factors

Countries with better economic conditions typically have more financial and technological resources, integrated supply chains, and advanced infrastructure. These advantages may lower deployment costs for renewable energy technologies, such as onshore wind, through reduced capital and operation and maintenance costs; economies of scale and learning effects; and improved project execution, thereby lowering LCOE. In an empirical study using random effects GLS on panel data for 27 EU member states (2011–2020), [Tu et al. \(2022\)](#) show that economic growth is positively associated with renewable energy deployment. While the study examines deployment rather than cost, this result accords with the previously noted channels through which better economic conditions can lead to higher deployment and ultimately lower LCOE. Furthermore, [Radmehr et al. \(2021\)](#), using panel spatial simultaneous equations for EU countries (1995–2014), provide evidence of positive spatial correlations among economic growth, CO₂ emissions, and renewable energy consumption. The study also finds that economic growth exhibits the strongest spatial dependence and a bidirectional relationship with renewable energy consumption. These results imply spatially connected energy markets, in which economic activity and renewable energy outcomes are closely linked across borders. Although the focus is on consumption rather than cost, this cross-border co-movement suggests that cost drivers linked to economic factors may also spill over, with implications for LCOE. Based on these theoretical mechanisms and the available empirical evidence, we formulate the following hypothesis: **H1:** Stronger economic performance is associated with lower onshore wind LCOE, both domestically and through spatial spillovers.

2.2. Social factors

Social factors may influence onshore wind LCOE through two contrasting mechanisms. Countries with higher human development tend to have advanced healthcare and education systems as well as a more skilled labor force. These advantages, for instance, can improve project efficiency and reduce operational risks, thereby lowering LCOE. However, LCOE can also increase as these countries experience higher wages and stricter regulations, which in turn raise construction and operating costs. As a result, our expectation for the direction of the relationship between social factors and onshore wind LCOE is uncertain. Direct cross-country evidence on the relationship between social factors and onshore wind LCOE is rare in the literature. However, using a Spatial Durbin Model for 30 Chinese provinces (2006–2021), [Chang et al. \(2024\)](#) find that higher levels of human capital are associated with lower carbon emissions both directly within a province and indirectly via spatial spillovers to neighboring provinces. This evidence suggests that social

factors can diffuse spatially and provides a rationale for incorporating social factors into our onshore wind LCOE framework. Given these competing mechanisms and the evidence of spatial interactions in social factors, we formulate the following hypothesis:

H2: Human development is associated with onshore wind LCOE, both domestically and through spatial spillovers, although the direction of the relationship is theoretically ambiguous.

2.3. Environmental factors

Variations in environmental factors may affect onshore wind LCOE in opposite directions due to different forces at play. For instance, high emission intensity often reflects limited decarbonization or continued reliance on fossil fuels. This situation may hinder renewable energy integration, potentially raising investment costs and LCOE. Conversely, in certain environmental contexts, higher emission intensity may be associated with high levels of industrialization and energy infrastructure, which can lower LCOE via economies of scale in deployment. Hence, our expectation for the direction of this relationship is uncertain. Empirical research that accounts for the spatial dimension indicates that environmental outcomes have strong cross-border effects. For instance, [Hunjra et al. \(2024\)](#) find that green innovation is positively associated with green total factor productivity, which spills over to neighboring areas. Another study shows that reliance on fossil fuels generates negative spatial spillovers for green economic growth, whereas renewable energy creates positive spillovers that enhance the sustainability of adjacent economies ([Miao et al., 2025](#)). Additional evidence from Europe and China indicates cross-border ecological spillovers ([Guliyev, 2024](#)) and spatial interactions in ecological footprint dynamics ([Zhang et al., 2024](#)). Taken together, these studies point to cross-border spatial interactions in environmental factors. Thus, cost drivers linked to environmental factors may also spill over, motivating their inclusion in our LCOE model. Given these competing mechanisms and the evidence of cross-border environmental interactions, we formulate the following hypothesis:

H3: Emission intensity is associated with onshore wind LCOE, both domestically and through spatial spillovers, although the direction of the relationship is theoretically ambiguous.

2.4. Institutional factors

Institutional factors may affect onshore wind LCOE through two competing channels. On one hand, higher institutional performance (e.g., transparent rules, effective legal enforcement, low corruption, and political stability) can reduce uncertainty, increase investor confidence, and streamline administrative processes. These, in turn, can help attract capital and decrease financing and deployment costs, thereby reducing LCOE. On the other hand, stronger institutions can also impose stricter permitting and mandatory transparency processes as well as more stringent environmental and labor regulations. As a byproduct, these requirements can also increase overall costs and lengthen permit approval timelines, thereby raising LCOE. Therefore, we have no clear expectation regarding the direction of this relationship. In line with these channels, [Diógenes et al. \(2020\)](#) state that political commitment is a necessary condition for successful support schemes promoting wind energy deployment. Moreover, [Kumar et al. \(2016\)](#) underline the need for a stable, transparent, and predictable policy environment to facilitate the expansion of wind energy deployment. Similarly, [Tu et al. \(2022\)](#) report that active political engagement and greater economic freedom are positively associated with renewable energy development. Complementing these findings, [Zahid et al. \(2025\)](#) highlight the importance of financial incentives, well-designed support schemes, innovative market frameworks, and resilient business models in enabling renewable energy adoption across sectors, thereby potentially lowering LCOE through financing and risk channels. Beyond domestic impacts, [Abrell and Kosch \(2022\)](#) show that renewable energy policies in one country

create spillover effects on the deployment patterns and marginal pricing in neighboring countries; thus, the findings suggest that institutional factors can generate cost-related spillovers across borders. Overall, these pieces of evidence provide a strong rationale for including institutional factors in our model. Based on these competing institutional mechanisms and the evidence of cross-border policy spillovers, we formulate the following hypothesis:

H4: Institutional performance is associated with onshore wind LCOE, both domestically and through spatial spillovers, although the direction of the relationship is theoretically ambiguous.

3. Data descriptions

3.1. Sample construction, data sources, and variables

In this research, we use a balanced annual panel dataset covering 10 OECD European countries—France, Germany, Greece, Ireland, Italy, the Netherlands, Poland, Spain, Sweden, and the United Kingdom—over the period 2011–2023. We first select countries based on data availability and spatial proximity, and then select the longest consistent time period for which data are available across all countries.¹ In total, the analysis is based on five panel data sources, one polygon-based shapefile, and one dataset of capital city centroids. To compare values across countries and time, we convert all monetary variables to constant 2023 USD using country-specific exchange rates and GDP deflators from the World Bank.

One of the key variables for onshore wind energy generation costs is LCOE, which serves as the dependent variable throughout this study. The LCOE data in constant 2023 USD/kWh are collected from IRENA (IRENA, 2024). However, due to missing observations for some countries and years, we apply monotonic cubic interpolation² to fill in missing values between two observed years. This procedure fills 5 missing observations and allows us to construct a balanced panel.

We use four macro-level factors—economic, social, environmental, and institutional—as explanatory variables for LCOE. First, economic factors are captured by the Gross Domestic Product per capita (GDP) from the World Bank (World Bank, 2026). GDP serves as a proxy for a country's overall economic performance. Second, social factors are captured by the Human Development Index (HDI) developed by the United Nations Development Programme (UNDP, 2025). As a composite indicator of long-term investments in health, education, and human capital, HDI serves as a proxy for the social factor considered in this study (i.e., human development). It ranges from 0 to 1, with higher HDI values indicating higher levels of human development. Third, environmental factors are captured by Greenhouse Gas Emissions per capita (GHG) from the World Development Indicators (World Bank, 2026). Specifically, we use total greenhouse gas emissions (excluding land-use, land-use change, and forestry) measured in tonnes of CO₂ equivalent per capita. As an emissions intensity measure, GHG reflects a country's emissions profile and its dependence on carbon-intensive economic and energy activities, thereby serving as a proxy for the environmental factor considered in this study. Finally, institutional factors are captured by a Governance Readiness Index (GRI), which we construct using four of the Worldwide Governance Indicators (WGI) from the World Bank (World Bank, 2025): political stability, control of corruption, regulatory quality, and rule of law. With the 2025 revision, the WGI began reporting an additional data series that provides values for the six governance dimensions on an absolute 0–100 scale, explicitly designed for cross-country and over-time comparisons. We use this new series and compute GRI as the unweighted mean of the four selected indicators. Accordingly, GRI ranges from 0 to 100, with higher values indicating better institutional performance. The resulting GRI reflects a country's institutional capacity to maintain a stable, predictable, and reliable investment environment. Therefore,

GRI serves as a proxy for the institutional factor considered in this study (i.e., institutional performance).

To account for additional factors that may confound the relationship between the four macro-level factors and LCOE, we include three control variables capturing wind industry development, energy market fundamentals, and technical progress. First, wind industry development is represented by Cumulative Onshore Wind Electricity Generation (WEGC), constructed from annual generation data obtained from IRENA (IRENA, 2026a). This measure captures accumulated operating experience in the onshore wind sector, consistent with the use of cumulative generation as an alternative experience measure in Schauf and Schwenen (2021). Second, energy market fundamentals are represented by the Renewable Electricity Generation Share (REGS), also obtained from IRENA (IRENA, 2026a). This variable captures the importance of renewable sources in a country's electricity generation mix. Finally, technical progress is represented by Cumulative Wind Energy Patents (WEPC), constructed using annual patent data from the OECD (OECD, 2026). Patent accumulation provides a proxy for the stock of technological knowledge related to wind energy, consistent with the use of patent-based knowledge stocks in the wind energy learning literature (Schauf and Schwenen, 2021). Together, these three variables allow us to account for differences in accumulated wind sector experience, electricity market conditions, and technological knowledge across countries and over time.

3.2. Summary statistics

Prior to integrating a spatial dimension into our panel data, we examine its characteristics as a preliminary step. Before proceeding, note two points about data transformation and notation. We transform all variables using natural logarithms to facilitate elasticity-based interpretations in the spatial panel models. To maintain conciseness and avoid repetition, we label all variables in the text, tables, and figures without indicating their units or logarithmic transformation, unless otherwise specified to clarify notation. Table 1 reports summary statistics of the transformed variables along with their overall, between, and within variations (i.e., SD_o , SD_b , and SD_w). The variation measures reveal an important characteristic of the panel data. LCOE exhibits substantial within-country variation ($SD_w = 0.40$), which considerably exceeds its between-country variation ($SD_b = 0.11$). In contrast, the four core explanatory variables—GDP, HDI, GHG, and GRI—are primarily characterized by between-country variation, with their between-country standard deviations exceeding their within-country counterparts. A similar pattern is observed for the control variables WEGC, REGS, and WEPC, although WEGC and REGS exhibit greater within-country variation than the four core explanatory variables. Overall, the panel combines substantial temporal variation in LCOE with predominantly cross-country heterogeneity in the explanatory variables. A brief discussion of the thematic mapping of all variables is deferred to Section 4.2, where we also examine spatial autocorrelation.

3.3. Spatial data

In addition to the panel data, we employ two types of spatial information to support the econometric analysis. First, we obtain a high-resolution polygon-based shapefile from the World Bank (World Bank, 2020). It is provided in unprojected geographic coordinates (EPSG:4326). Using geometric simplification methods, we create a low-resolution shapefile, which is a version of the high-resolution shapefile with fewer vertices. Throughout the paper, we use the high-resolution shapefile for all econometric estimations and reserve the low-resolution version for thematic mapping only. To improve spatial clarity, we exclude all subcountry regions located more than 200 km from their respective mainlands (e.g., French Guiana and overseas territories) from the low-resolution shapefile used for mapping. We then project the low-resolution shapefile to a coordinate reference system optimized for Europe (EPSG:3035). Second, we use capital city centroids as

¹ We use the most recent publicly available data as of August 2026.

² Monotonic cubic interpolation is preferred since it preserves the shape and direction of the original series and avoids generating unrealistic fluctuations.

Table 1
Summary Statistics.

	N	Min	Max	Mean	SD _w	SD _b	SD _o
LCOE	130	-3.61	-1.77	-2.65	0.40	0.11	0.41
GDP	130	9.58	11.62	10.60	0.10	0.47	0.45
HDI	130	-0.15	-0.04	-0.09	0.01	0.03	0.03
GHG	130	1.58	2.70	2.13	0.10	0.27	0.28
GRI	130	4.05	4.48	4.31	0.02	0.12	0.12
WEGC	130	15.90	21.02	18.62	0.61	0.98	1.12
REGS	130	-2.51	-0.37	-1.27	0.31	0.42	0.51
WEPC	130	3.78	8.92	6.26	0.22	1.31	1.27

Notes: LCOE, GDP, HDI, GHG, GRI, WEGC, REGS, and WEPC indicate Levelized Cost of Electricity for Onshore Wind, Gross Domestic Product per capita, Human Development Index, Greenhouse Gas Emissions per capita, Governance Readiness Index, Cumulative Onshore Wind Electricity Generation, Renewable Electricity Generation Share, and Cumulative Wind Energy Patents, respectively. SD_w , SD_b , and SD_o refer to within, between, and overall standard deviations, respectively. All variables are in natural logarithms.

spatial reference points when constructing spatial linkages across countries. These centroids are collected from the countryref dataset in the CoordinateCleaner package (CoordinateCleaner, 2025) for R. Fig. 1(a) shows the projected shapefile with capital city centroids. For all maps in this study, map lines delineate study areas and do not necessarily depict accepted national boundaries.

4. Empirical methods

4.1. Contiguity and weight matrices

Before conducting spatial analyses with areal data (i.e., spatial polygons), two assumptions must be made about the structure of the spatial process: (1) the contiguity type, which specifies the notion of a neighbor; and (2) the weight style, which determines how neighbors influence each other. A contiguity type specifies neighbor links between areal units using an $N \times N$ contiguity matrix C , where $c_{ij} = 1$ if units i and j are neighbors ($i \neq j$), and $c_{ij} = 0$ otherwise, with $i, j = 1, \dots, N$ indexing units. The resulting contiguity matrix is then converted into a

nonnegative $N \times N$ spatial weight matrix W based on the chosen weight style. The weight matrix is used to construct spatially lagged variables, which are essential in spatial autocorrelation tests and spatial econometric models. For a comprehensive review of these assumptions, see Anselin (1988); Bavaud (1998); Zhukov and Stewart (2013).

In this study, we adopt a graph-based approach and construct neighbor links using Delaunay Triangulation contiguity. In contrast to adjacency-based contiguities (e.g., Queen and Rook), Delaunay Triangulation defines neighbor links by forming a planar graph based on interpoint distances, thus avoiding the exclusion of links caused by geographic discontinuities (e.g., coastlines). This allows for more flexible modeling of spatial interactions when geographic continuity is disrupted or irrelevant. For example, some countries in our sample (e.g., the United Kingdom) are geographically separated from others, yet can have economic or institutional ties with proximate countries. For interpoint distance calculations, we use capital city centroids rather than geographic centroids, as they better represent national centers of policy and investment decision-making for onshore wind energy development. In contrast, geographic centroids may lie in uninhabited regions (e.g., offshore waters) and may therefore be less informative for modeling spatial interactions. Fig. 1(b) visualizes the resulting neighbor links based on Delaunay Triangulation contiguity.

Using the contiguity matrix based on Delaunay Triangulation, we construct the benchmark spatial weight matrix with a row-standardized weight style, in which the weights assigned to each unit's neighbors sum to one. This weighting style is commonly used in spatial econometric applications due to its computational properties, which simplify Quasi-Maximum Likelihood (QML) estimation. We denote this benchmark spatial weight matrix by DT. We also consider alternative spatial weight matrices as robustness checks. These alternative matrices differ from the benchmark in their underlying neighborhood structures (i.e., contiguity types), the distance-based weighting scheme applied before row-standardization, or both. As with the benchmark matrix, the alternative spatial weight matrices are ultimately row-standardized to maintain a consistent weighting style across all matrices. These alternative spatial weight matrices are discussed in Appendix A.

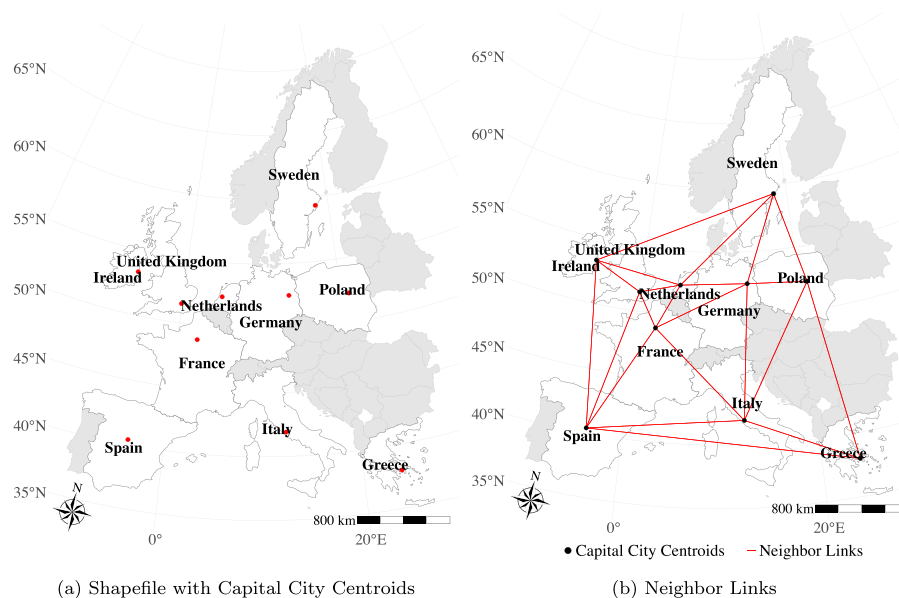


Fig. 1. Shapefile and neighbor links based on Delaunay triangulation contiguity.

4.2. Spatial autocorrelation tests

A necessary condition for applying spatial econometric models is the presence of spatial autocorrelation³ in the data. According to LeSage and Pace (2009), ignoring spatial structure may yield coefficient estimates that are both biased and inconsistent, whereas imposing overly complex spatial structures may lead to inefficiency. Therefore, testing for spatial autocorrelation is an essential preliminary step before estimating spatial panel models.

As a preliminary diagnostic for formal spatial autocorrelation tests, we explore spatial patterns in all variables via thematic maps. Fig. 2 shows the spatial patterns in LCOE and the four core explanatory variables for 2011, 2017, and 2023, representing the start, midpoint, and end of the study period. The thematic maps for the three control variables (WEGC, REGS, and WEPC) are reported in Fig. B.5 in Appendix B. The patterns shown in Fig. 2 reveal noticeable spatial variation in LCOE and in the four core explanatory variables, although their strength and persistence vary across countries and over time. For example, GDP and HDI exhibit relatively persistent spatial patterns, whereas LCOE displays more pronounced changes over the study period. GHG and GRI also show spatial variation across countries and years. These visual patterns provide an empirical basis for undertaking formal tests for spatial autocorrelation.

Moran's I, originally developed by Moran (1950), is the standard spatial autocorrelation test for areal data. It assesses whether neighboring units tend to have similar values more often than expected under the assumption of no spatial autocorrelation. The Moran's I test statistic ranges from -1 (perfect spatial dispersion) to $+1$ (perfect spatial clustering). There are three methods for implementing the Moran's I test: randomization, Monte Carlo simulation, and the normality assumption (Cliff and Ord, 1972). Among these, randomization is particularly effective for small to medium sample sizes because it does not require distributional assumptions (Anselin and Florax, 1995).

We perform Moran's I tests following the randomization method to assess the presence and strength of spatial autocorrelation in the core variables of our study.⁴ Fig. 3 displays the Moran's I statistics over time, highlighting temporal trends for the core variables. The results for GDP, HDI, and GRI exhibit positive and statistically significant spatial autocorrelation that persists throughout the sample period, suggesting persistent spatial clustering. In contrast, GHG exhibits negative and statistically significant spatial autocorrelation throughout the sample period, indicating spatial dispersion rather than clustering. Spatial autocorrelation in our dependent variable, LCOE, varies considerably over time. It is positive and statistically significant in 2012, 2013, 2015, 2016, and 2018; negative and statistically significant between 2019 and 2021; and positive and statistically significant again in 2023. Although these tests are based on cross-sectional data and do not explicitly account for the panel data structure of our study, the evidence of statistically significant spatial autocorrelation across variables and years suggests that spatial effects are non-negligible. Therefore, further investigation through spatial panel models is required.

4.3. Spatial panel models

Spatial panel models can be viewed as extensions of standard panel models that incorporate spatial dependence into the modeling framework. Thus, in the absence of the spatial dimension, the standard panel model can be written as:

$$Y_t = X_t\beta + \mu + \xi_t'N + \varepsilon_t \quad (1)$$

³ Spatial autocorrelation and its stronger form, spatial dependence, are not identical concepts but are often used interchangeably. The former refers to the correlation of variables across space, while the latter describes a structural spatial relationship in econometric models.

⁴ In all Moran's I tests, we use a right-tailed hypothesis, as negative spatial autocorrelation is rare in empirical applications.

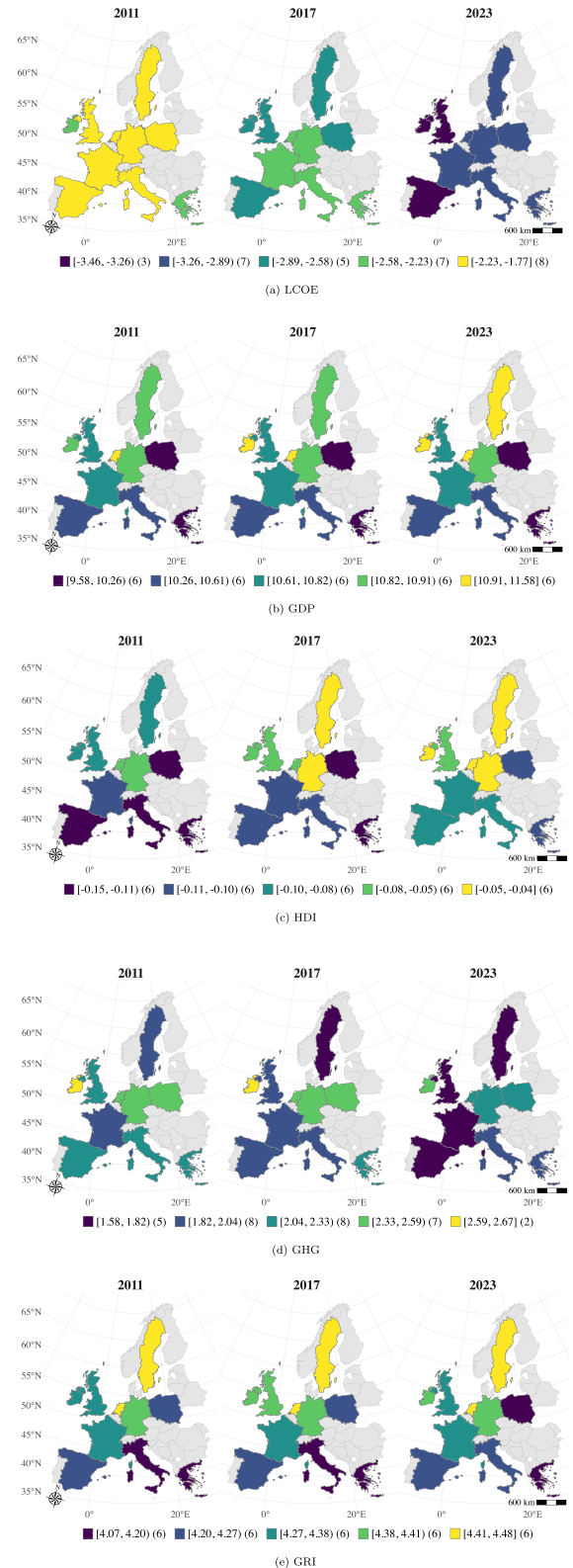


Fig. 2. Thematic maps of LCOE and core variables.

where Y_t denotes an $N \times 1$ vector of the dependent variable for all units $i = 1, \dots, N$ at time $t = 1, \dots, T$; X_t is an $N \times K$ matrix of K explanatory variables at time t ; β denotes a $K \times 1$ column vector containing the coefficients of the K explanatory variables; ε_t denotes an $N \times 1$ vector

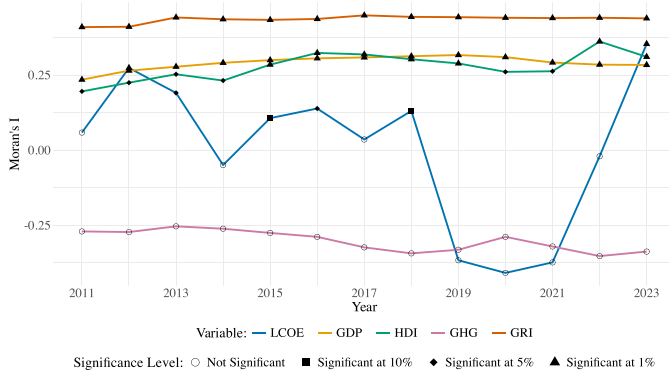


Fig. 3. Moran's I test statistic over time for LCOE and core variables.

of random errors at time t with $\varepsilon_{it} \sim (0, \sigma^2)$; $\mu = (\mu_1, \dots, \mu_N)'$ and $\xi_{it} \sim (0, \sigma^2)$ are $N \times 1$ vectors capturing unobserved individual and time-specific heterogeneity, respectively; and t_N denotes an $N \times 1$ vector of ones. These unobserved heterogeneities can be modeled as either fixed or random effects, yielding the fixed effects and random effects panel models. Under the fixed effects model, these heterogeneities are represented by dummy variables for each cross-sectional unit and each time period. In contrast, the random effects model treats them as random variables with $\mu_i \sim (0, \sigma_\mu^2)$ and $\xi_{it} \sim (0, \sigma_\xi^2)$, where μ_i , ξ_{it} , and ε_{it} are mutually independent.

Although the panel model in Eq. (1) accounts for unobserved individual and time-specific heterogeneity, it implicitly assumes that each unit evolves independently of its neighbors. In other words, it ignores spatial interactions arising from spatial proximity, which can be overly restrictive in empirical applications. Hence, Eq. (1) serves as the baseline panel data model on which spatial panel econometric models are built by explicitly adding spatial interactions.

As Manski (1993) notes, spatial interaction effects can enter panel models through three distinct sources: (1) endogenous interaction effects (i.e., y_i depends on y_j for $i \neq j$), denoted by the spatially lagged dependent variable WY_t ; (2) exogenous interaction effects (i.e., y_i depends on x_j for $i \neq j$), denoted by the spatially lagged explanatory variables WX_t ; and (3) interaction effects among the error terms, denoted by the spatially lagged error terms Wu_t , where W is a nonnegative $N \times N$ spatial weight matrix and u_t is an $N \times 1$ vector of error terms at time t (Elhorst, 2010). Spatial panel models can incorporate one or more of these interaction effects, either individually or in combination.

A model that incorporates all spatial interaction effects into the standard panel model in Eq. (1) is called the General Nesting Spatial Model (GNS). Its general form is:

$$Y_t = \rho WY_t + X_t\beta + WX_t\theta + \mu + \xi_{it}t_N + u_t, \quad u_t = \lambda Wu_t + \varepsilon_t \quad (2)$$

where θ denotes a $K \times 1$ vector containing the spatial spillover parameters linked to the K explanatory variables; ρ and λ are the spatial dependence parameters, commonly referred to as spatial autoregressive and spatial autocorrelation parameters, respectively; and all other notation follows Eq. (1).

Fig. 4 provides an overview of spatial panel models and clarifies the structural relationships among them using a general-to-specific approach. Each model nested within GNS, shown to the right, can be derived by imposing the parameter restrictions indicated by arrows. These restricted models can be estimated using QML, which does not require the assumption of normally distributed error terms.

Among the spatial panel models in Fig. 4, GNS appears to be the best starting point, as it includes all spatial interaction effects simultaneously. However, it suffers from overfitting and identification issues (Elhorst, 2010). In contrast, SDM avoids these issues by excluding interaction effects among the error terms and is considered the most suitable choice in applied studies (LeSage and Pace, 2009). While omitting interaction effects in the dependent and/or explanatory variables may result in biased and inconsistent coefficient estimates, excluding interaction effects among the error terms does not bias the estimates but reduces efficiency. For instance, treating SDEM as the initial spatial model will lead to omitted variable bias if the true data-generating process (DGP) corresponds to SDM, SAR, or SAC. By contrast, SDM delivers unbiased coefficient estimates even when the true DGP corresponds to any of the alternative spatial panel models shown in Fig. 4, excluding GNS.

While the SDM is often regarded as the most robust specification from a theoretical perspective, applied studies in the literature typically rely on formal statistical methods for model selection. The first method uses Lagrange Multiplier (LM) tests to evaluate whether SAR or SEM is more appropriate than a non-spatial panel model (Anselin et al., 2008; Elhorst et al., 2010). The standard LM tests, LM_ρ and LM_λ , examine the existence of spatial interactions in the dependent variable and in the error terms, respectively. Their robust counterparts, LM_ρ^* and LM_λ^* , test for one type of spatial interaction effect while controlling for the other, thereby allowing for more reliable model specification decisions when multiple spatial interaction effects coexist. The second method involves Wald-type tests to assess the validity of parameter restrictions across nested models (Elhorst, 2014). The third method compares both nested and non-nested models using log-likelihood (LL) values and information criteria such as Akaike Information Criterion (AIC) and Bayesian

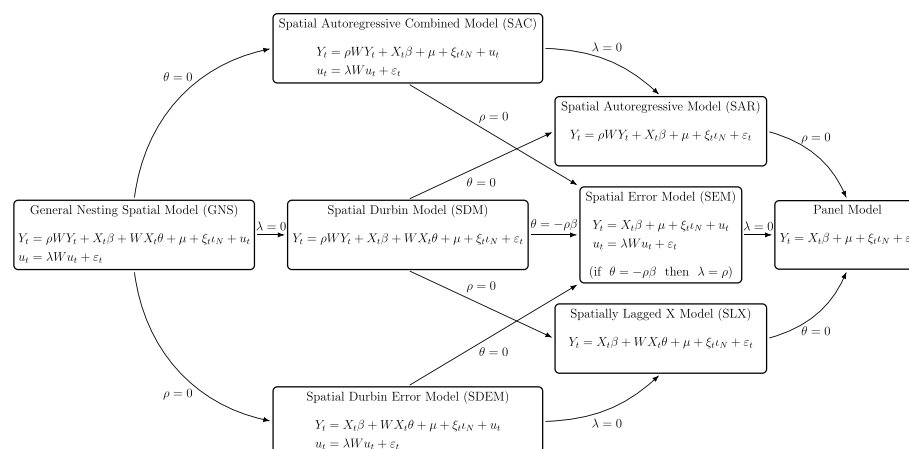


Fig. 4. Spatial Panel Models.

Information Criterion (BIC) (Hoeting et al., 2006). Fourth, in the presence of model uncertainty, LeSage (2014) suggests using Bayesian Model Comparison (BMC), which does not rely on asymptotic test statistics or the assumption of nested models. Based on observed data and prior beliefs, BMC compares alternative non-spatial and spatial panel models by computing their log-marginal likelihoods and posterior model probabilities.

A key strength of spatial panel models is their ability to measure spillover effects, whereby changes in unit i influence neighboring unit j ($i \neq j$). To demonstrate how spatial spillovers work, consider the reduced form of the SDM given by

$$Y_t = (I_N - \rho W)^{-1}(X_t \beta + W X_t \theta) + (I_N - \rho W)^{-1}(\mu + \xi_t I_N + \varepsilon_t) \quad (3)$$

where I_N is an $N \times N$ identity matrix. Using the infinite series expansion, the $N \times N$ matrix containing the partial derivatives of the expectation of Y_t , $E(Y_t)$, with respect to the k^{th} explanatory variable in X_t across all N units can be defined as:

$$\left[\frac{\partial E(Y_t)}{\partial x_{1k}} \quad \dots \quad \frac{\partial E(Y_t)}{\partial x_{Nk}} \right] = (I_N - \rho W)^{-1}(I_N \beta_k + W \theta_k) \quad (4)$$

$$= (I_N + \rho W + \rho^2 W^2 + \dots) \begin{bmatrix} \beta_k & w_{12}\theta_k & \dots & w_{1N}\theta_k \\ w_{21}\theta_k & \beta_k & \dots & w_{2N}\theta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}\theta_k & w_{N2}\theta_k & \dots & \beta_k \end{bmatrix} \quad (5)$$

where w_{ij} is the $(i, j)^{\text{th}}$ entry in the spatial weight matrix W . In Eq. (5), the diagonal elements represent the direct impacts (i.e., how changes in x_{ik} influence y_i), whereas the off-diagonal elements represent the indirect impacts or spatial spillovers (i.e., how changes in x_{ik} influence y_j for $i \neq j$). These impacts are independent of t , assuming the spatial weight matrix W does not change over time. Given the complexity of the K distinct $N \times N$ derivative matrices, LeSage and Pace (2009) suggest summarizing these impacts through three interpretable average impact measures: (1) the mean of the diagonal elements capturing direct impacts; (2) the mean across rows or columns of off-diagonal elements capturing indirect impacts; and (3) the mean across all values representing total impacts. As proposed by LeSage and Pace (2009), statistical inference on these impacts can be performed using Monte Carlo simulations.

In spatial panel models, it is also possible to distinguish between global and local spillover effects. Global spillovers (requiring $\rho \neq 0$) arise from the infinite series expansion, such as $(I_N - \rho W)^{-1}$ in Eq. (4). The most important implication of global spillovers is that a change in x_{ik} affects not only y_i but also y_j for all $j \neq i$, regardless of whether units i and j are first-order (direct) neighbors. This global mechanism also gives rise to feedback effects, where changes originating in one unit circulate through higher-order neighbors and eventually feed back to the originating unit (e.g., a path from x_{1k} to y_1 , to y_2 , to y_3 , to y_2 , and back to y_1). In contrast, local spillovers (requiring $\theta \neq 0$) occur only between directly connected units and thus do not generate feedback effects. While global spillovers lose strength as they reach higher-order neighbors, local spillovers die out before affecting second-order neighbors. In the context of impact measures, feedback effects are captured by direct impacts, whereas global and local spillovers are captured by indirect impacts.

5. Results and discussion

5.1. Model selection strategy

To determine the most suitable spatial panel model for our data, we follow a stepwise model selection strategy, which provides a statistical rationale for introducing additional components (i.e., unobserved heterogeneity and spatial interactions) to our econometric framework. Our strategy increases model complexity at each step, starting with the pooled model, proceeding to panel models, and finally extending the selected panel specification to alternative spatial panel models. During model selection, candidate models are estimated using conventional

standard errors, as the LM and Wald-type tests are implemented under a likelihood-based estimation framework that relies on a conventional variance-covariance matrix (LeSage and Pace, 2009; Elhorst, 2014). The corresponding results are reported in Table 2.⁵ Once the preferred spatial panel model is selected, we re-estimate it for inference using Driscoll-Kraay standard errors, which are robust to heteroskedasticity, serial correlation, and general forms of cross-sectional dependence (Driscoll and Kraay, 1998).

Ignoring these additional components, we begin with a pooled model, which serves as the reference point for selecting the appropriate non-spatial panel model. We first test the pooling assumption separately for individual and time effects following Wooldridge (2010). Both tests reject the pooled model, indicating the presence of unobserved individual ($z = 2.03$, $p = 0.043$) and time-specific ($z = 2.62$, $p = 0.009$) heterogeneity. We then test the same assumption using LM and F tests for individual, time, and joint effects (Breusch and Pagan, 1980; Baltagi, 2021). All of these tests yield the same conclusion and provide further evidence against the pooled model. Therefore, based on the above evidence, we move on to the non-spatial panel models.

Among the non-spatial panel models, we first determine whether fixed effects (FE) or random effects (RE) provide the more appropriate model. To provide formal empirical evidence for this choice, we perform three Hausman tests, one for each of the individual, time, and joint effects (Hausman, 1978). All three tests reject the RE model at the 1% significance level, supporting the corresponding FE models. Finally, we determine whether to incorporate individual, time, or joint effects into the FE model. The F test for the addition of time effects to the individual FE model rejects the null hypothesis at the 5% significance level ($F = 1.90$), while the corresponding test for the addition of individual effects to the time FE model rejects the null at the 1% level ($F = 5.53$). Taken together, these results support the two-way FE model, which accounts for both unobserved individual and time-specific heterogeneity. Therefore, we use the two-way FE model as our baseline non-spatial panel model, hereafter referred to as the baseline FE model, against which we evaluate the spatial panel models.

Before introducing spatial interaction effects, we perform diagnostic tests on the residuals of the baseline FE model. First, Wooldridge's AR(1) and Breusch-Godfrey LM tests provide strong evidence of serial correlation in the idiosyncratic errors (Breusch, 1978; Godfrey, 1978; Wooldridge, 2010). Second, the global Cross-sectional Dependence test rejects the null hypothesis of cross-sectional independence ($z = -2.44$) at the 5% significance level (Pesaran, 2004). Overall, these diagnostics indicate the presence of serial correlation and general cross-sectional dependence, which provide the rationale for our use of Driscoll-Kraay standard errors for inference in the preferred spatial panel model.

In the next step, we extend the baseline FE model by incorporating alternative spatial interaction effects. We estimate SAR, SEM, SAC, and SDM specifications using QML with the benchmark spatial weight matrix DT.⁶ The corresponding model results are reported in Table 2.

To identify the best spatial panel model, we employ a model selection strategy consisting of four complementary methods. First, standard LM tests and their robust counterparts are applied to compare the baseline FE model, SAR, and SEM. Both standard LM_ρ ($LM = 4.70$) and LM_λ ($LM = 5.10$) tests are statistically significant at the 5% level, indicating that both SAR and SEM are preferable to the FE model. Second, we run a series of Wald-type tests to compare nested spatial panel models based on the restrictions shown in Fig. 4. Our findings in Table 3 suggest that SAR, SEM, and SDM significantly outperform the FE model.

⁵ All models are estimated using the *xsmle* package in Stata (Belotti et al., 2017).

⁶ The SAC model does not achieve convergence under the baseline FE model and is therefore excluded from subsequent model comparisons. SLX is not directly estimated in *xsmle*, but is evaluated as a restricted form of SDM by imposing $\rho = 0$.

Table 2
Model Results.

	All Models:				
	Pooled	FE	SAR	SEM	SDM
GDP	0.54***	0.04	0.00	−0.18	−3.14***
HDI	−11.15***	4.77	3.86	5.98*	17.25*
GHG	0.42***	0.35	0.31	0.64	2.72***
GRI	−0.60	−0.21	−0.33	−0.87	−8.79***
WEGC	−0.43***	−0.24**	−0.19***	−0.33***	−2.02***
REGS	0.22**	0.29**	0.22***	0.39***	1.29***
WEPC	0.35***	−0.99**	−0.73***	−1.19***	−6.10***
Obs.	130	130	130	130	130
ρ			−0.36**		−0.47***
λ				−0.48***	
R^2_w		0.89†	0.84	0.86	0.86
R^2_b		0.00	0.00	0.00	0.01†
R^2_o	0.57†	0.05	0.01	0.03	0.16
LL	−14.2	79.4	82.4	83.6	99.6†
AIC	44.3	−118.8	−146.9	−149.1	−167.2†
BIC	67.3	−61.5	−121.1	−123.3†	−121.3

Notes: LCOE is the dependent variable in all models. The coefficient estimates reported for SAR and SDM correspond to total impacts. Conventional standard errors are used in all models. R^2_w , R^2_b , and R^2_o refer to within, between, and overall R^2 , respectively. † denotes the best-performing model according to the model selection criterion reported in each row. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3
Tests for nested Models.

Comparison	H_0	χ^2 Statistic	Decision
FE vs. SAR	$\rho = 0$	6.30**	SAR
FE vs. SEM	$\lambda = 0$	8.48***	SEM
FE vs. SDM	$\rho = 0, \theta = 0$	49.50***	SDM
SAR vs. SDM	$\theta = 0$	39.96***	SDM
SEM vs. SDM	$\theta = -\beta\rho$	32.61***	SDM
SLX vs. SDM	$\rho = 0$	10.53***	SDM

Notes: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Furthermore, SDM is found to significantly outperform simpler spatial alternatives such as SAR, SEM, and SLX.⁷ Third, we compare the candidate models using LL, AIC, and BIC. The results in Table 2 show that LL and AIC favor SDM, while BIC slightly favors SEM over SDM. Fourth, BMC provides further support for SDM. Its results show that SDM (log-marginal likelihood = 41.09 and posterior model probability = 0.629) substantially outperforms all other candidate models, including the FE model, SAR, SEM, SLX, and SDEM. Overall, these results provide strong support for the Spatial Durbin Model as the preferred spatial panel model for subsequent inference.

5.2. Spatial durbin model results and impact estimates

We now turn to a detailed examination of the SDM. The overall model statistics of the SDM, along with coefficient estimates representing total impacts prior to their decomposition, are reported in Table 2. Although the estimated spatial autoregressive coefficient ($\rho = -0.47$) is moderate in magnitude, it is statistically significant at the 1% level, indicating the presence of spatial interactions in the dependent variable. The R^2_w value of 0.86 indicates that the SDM explains a substantial share of the within-country variation in the dependent variable over time, although it is slightly lower than the 0.89 obtained from the baseline FE model. The R^2_b remains low at 0.01, while the overall R^2_o increases from 0.05 in the

FE model to 0.16 in the SDM. Moreover, the LL, AIC, and BIC values consistently favor the SDM over the baseline FE model.

The estimated direct, indirect, and total impacts of the SDM are presented in Table 4.⁸ Since all variables in the model are in natural logarithms, the impact estimates of the explanatory variables represent elasticities and are interpreted as percentage changes. As the implications of impact estimates differ across the explanatory variables, we examine each in detail in several steps: (1) interpreting the total impact estimates; (2) highlighting whether the total impacts are primarily driven by direct impacts (i.e., domestic channel) or indirect impacts (i.e., spatial spillover channel); and (3) discussing whether the findings support our central hypothesis, whether they align with our initial theoretical expectations, and how they relate to the channels and mechanisms discussed in the literature review.

The total impact estimate of GDP on LCOE is negative and statistically significant at the 1% level, indicating that a 1% rise in GDP is associated with an approximately 3.12% reduction in LCOE. This is consistent with our expectation that stronger economic performance may lower deployment costs and, in turn, lower the LCOE. The decomposition of the total impact reveals that both the direct and indirect impacts are negative and statistically significant at the 1% level. The direct impact estimate (−0.86%) indicates that improvements in domestic economic performance are associated with a reduction in a country's own LCOE. The indirect impact estimate (−2.25%), which is larger in magnitude, indicates that improvements in neighboring countries' economies are also associated with a reduction in a country's own LCOE through spatial spillovers. Thus, while both domestic and spatial channels contribute to the negative total impact of GDP, the larger indirect impact suggests that the spatial spillover channel plays a particularly important role.

For HDI, the total impact estimate is positive and statistically significant at the 10% level, indicating that a 1% rise in HDI is associated with an approximately 17.19% increase in LCOE. The decomposition provides a clearer picture of the underlying channels. The direct impact estimate (10.80%) is positive and statistically significant at the 1% level, indicating a strong positive association between domestic human development and a country's own LCOE. In contrast, although the indirect impact estimate is also positive (6.39%), it is not statistically significant. Therefore, the results provide evidence that the positive relationship between HDI and LCOE is primarily associated with the domestic channel, while there is no statistically significant evidence of a spatial spillover effect.

Our GHG results indicate that the total impact estimate is positive and statistically significant at the 5% level. Specifically, a 1% increase in GHG emission intensity is associated with an approximately 2.71% increase in LCOE. The decomposition reveals that both channels contribute to this positive relationship. The direct impact estimate (0.82%) is positive and statistically significant at the 5% level, indicating that higher domestic emission intensity is associated with higher domestic LCOE. Similarly, the indirect impact estimate (1.89%) is positive and statistically significant at the 5% level, indicating that higher emission intensity in neighboring countries is also associated with higher domestic LCOE through spatial spillovers. The indirect impact is larger than the direct impact, suggesting that the spatial spillover channel plays a larger role in the overall positive association between GHG and LCOE.

For GRI, the direct, indirect, and total impact estimates are all negative and statistically significant at the 1% level. Specifically, the total impact estimate indicates that a 1% increase in GRI is associated with an approximately 8.72% reduction in LCOE. The decomposition reveals

⁸ The small differences between the total impact estimates reported in Tables 2 and 4 arise from the Monte Carlo simulation implemented by the xsmle package in Stata for spatial impact estimation (Belotti et al., 2017). The simulated impacts depend on the variance-covariance matrix used to generate the parameter draws: Table 2 is based on conventional standard errors, whereas Table 4 uses Driscoll-Kraay standard errors. The estimated SDM parameters β , θ , and ρ in Eq. (3) remain unchanged.

⁷ Although SLX is not estimated directly, it is nonetheless tested as a restricted form of the SDM with $\rho = 0$.

Table 4
SDM Impacts.

	Impacts:		
	Direct	Indirect	Total
GDP	−0.86***	−2.25***	−3.12***
HDI	10.80***	6.39	17.19*
GHG	0.82**	1.89**	2.71**
GRI	−2.50***	−6.22***	−8.72***
WEGC	−0.70***	−1.33***	−2.03***
REGS	0.59***	0.70**	1.29***
WEPC	−2.81***	−3.28***	−6.09***

Notes: Statistical inference for the estimated impacts is based on 10,000 Monte Carlo simulations. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

that both domestic and spatial channels contribute to this negative relationship. The direct impact estimate (−2.50%) indicates that stronger domestic institutional performance is associated with lower domestic LCOE. The indirect impact estimate (−6.22%) is substantially larger in magnitude, indicating that improvements in neighboring countries' institutional performance are also associated with lower domestic LCOE through spatial spillovers. Thus, although both channels contribute to the negative total impact of GRI, the results suggest that the spatial spillover channel is the larger component of the overall association.

Turning to the control variables, the direct, indirect, and total impact estimates are statistically significant for WEGC, REGS, and WEPC. For WEGC, a 1% increase in cumulative onshore wind electricity generation is associated with an approximately 2.03% reduction in LCOE, with both the direct (−0.70%) and indirect (−1.33%) impacts contributing to this negative relationship. In contrast, the total impact of REGS is positive (1.29%), indicating that a higher renewable electricity generation share is associated with higher LCOE through both direct (0.59%) and indirect (0.70%) impacts. Finally, WEPC exhibits the largest total impact in magnitude among the three control variables: a 1% increase in cumulative wind energy patents is associated with an approximately 6.09% reduction in LCOE. This relationship is also reflected in both the direct (−2.81%) and indirect (−3.28%) impacts. Overall, the results indicate that accumulated wind sector experience and technological knowledge are negatively associated with LCOE, whereas a higher renewable electricity generation share is positively associated with LCOE.

A final comparison of the baseline FE model and the SDM highlights the importance of incorporating the spatial dimension when estimating the impact of macro-level factors on onshore wind LCOE. Specifically, when we compare the estimates of the baseline FE model with the SDM total impacts, we observe the following: (1) GDP shifts from 0.04 (insignificant) to −3.12 (significant); (2) HDI shifts from 4.77 (insignificant) to 17.19 (significant); (3) GHG shifts from 0.35 (insignificant) to 2.71 (significant); and (4) GRI shifts from −0.21 (insignificant) to −8.72 (significant). Thus, while none of the four core variables is statistically significant in the baseline FE model, their total impacts in the SDM are statistically significant, highlighting the importance of accounting for spatial spillovers when interpreting these relationships.

The estimated impacts should nevertheless be interpreted with caution due to potential endogeneity and reverse causality between LCOE and the macro-level factors. Although our two-way fixed effects model controls for time-invariant country heterogeneity and common time-specific shocks, and the additional control variables account for wind industry development, energy market fundamentals, and technical progress, these features do not fully address simultaneity. In particular, the relationships examined in this study may operate in both directions. Lower onshore wind LCOE may stimulate wind energy investment and deployment, which may subsequently affect economic activity and emissions, while changes in renewable energy investment

and deployment may also be associated with broader institutional and human development conditions. Reverse causality may therefore affect both the magnitude and, potentially, the direction of the estimated impacts. However, because these simultaneous channels can operate alongside omitted time-varying factors and spatial interactions, the direction of the resulting bias cannot be determined unambiguously without additional identifying assumptions. Therefore, our estimates should be interpreted as conditional associations rather than causal effects. Establishing causality would require an appropriate identification strategy, such as valid instruments. Such an analysis is beyond the scope of this study.

6. Conclusion and policy implications

This research investigates the relationship between macro-level factors—economic, social, environmental, and institutional—and onshore wind LCOE in European countries over time, while accounting for cross-country spatial dependence. Using a balanced annual panel of 10 OECD European countries from 2011–2023, we estimate a spatial panel model, specifically the Spatial Durbin Model with two-way fixed effects, which receives the strongest overall support among the non-spatial and spatial models considered. In this model, the relationships between macro-level factors and LCOE can operate not only within countries (i.e., domestic channel) but also across neighboring countries through cross-border spatial spillovers. Our results show that stronger economic performance and institutional performance are associated with lower LCOE through both domestic and spatial spillover channels, with the indirect impacts exceeding the direct impacts in magnitude. In contrast, higher emission intensity is associated with higher LCOE through both channels, again with a larger indirect impact. Human development is also positively associated with LCOE, although this relationship is primarily driven by the domestic channel, as its indirect impact is not statistically significant. The results for the control variables further show that higher cumulative onshore wind electricity generation and cumulative wind energy patents are negatively associated with LCOE, whereas a higher renewable electricity generation share is positively associated with LCOE. Overall, these findings show that accounting for spatial interactions substantially changes the estimated relationships between macro-level factors and onshore wind LCOE and reveals economically relevant cross-country spillovers that are not captured by the baseline two-way fixed effects model.

Our policy message is clear: onshore wind energy cost-reduction policies, particularly in Europe, should account for cross-country spatial dependence and should not be designed exclusively within national borders. We highlight four policy implications. First, stronger economic performance is associated with lower LCOE both domestically and through neighboring economies, highlighting the potential relevance of regional economic conditions for onshore wind energy costs. Second, the positive association between human development and LCOE is driven primarily by the domestic channel, suggesting that policymakers should consider the domestic cost implications of higher levels of human development when designing wind energy policies. Third, the positive direct and indirect impacts of emission intensity indicate that carbon-intensive economic and energy structures are associated with higher onshore wind costs both domestically and across neighboring countries, underscoring the relevance of coordinated regional decarbonization. Fourth, stronger institutional performance is associated with substantially lower LCOE through both domestic and spatial spillover channels, with the larger indirect impact suggesting that the associated benefits may extend beyond national borders.

As with any empirical analysis, our results are subject to limitations arising from data and methodological choices. Some limitations include: (1) the use of interpolation to address 5 missing LCOE observations (approximately 3.8% of the sample), which may introduce measurement error; (2) the specification of the spatial weight matrix, as alternative neighborhood structures and weighting schemes may represent different

forms of cross-country spatial interactions (although robustness analyses using three alternative spatial weight matrices indicate that the main findings are generally robust); and (3) potential endogeneity and reverse causality between the macro-level factors and LCOE, which limit a causal interpretation of the estimated relationships. Beyond these data and methodological limitations, it is also important to consider potential regional heterogeneity within Europe. Given the differences in economic, social, environmental, institutional, and energy market conditions across Europe, the estimated relationships and the relative emphasis placed on the corresponding policy measures may differ across Western, Eastern, Northern, and Southern European countries. Identifying such regional differences explicitly, however, would require region-specific empirical analysis.

Future research can build on our framework by employing identification strategies that directly address potential endogeneity, examining a broader range of spatial weight matrices, exploring regional heterogeneity through region-specific analyses, incorporating dynamic terms into the spatial panel model, expanding country coverage, and extending the analysis to other renewable technologies.

CRediT authorship contribution statement

Ömer Kara: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization, Visualization. **Hakan Acaroğlu:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Grammarly in order to assist with grammar and language editing. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

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

Appendix A. Alternative spatial weight matrices

To examine the sensitivity of our results to the specification of the spatial weight matrix, we consider three alternatives to the benchmark spatial weight matrix DT, which is constructed using Delaunay Triangulation contiguity. These alternative matrices differ from the benchmark along two dimensions: the underlying neighborhood structure (i.e., contiguity type) and the distance-based weighting scheme applied before row-standardization. Specifically, we consider DT-ID², SOI-ID, and K2-ID as alternative spatial weight matrices.

The DT-ID² spatial weight matrix retains the same Delaunay Triangulation contiguity as the benchmark but applies inverse-squared-distance weighting before row-standardization. Therefore, this specification holds the underlying spatial links fixed while imposing stronger distance decay, allowing us to examine whether the results are sensitive to the choice of distance-based weighting scheme. The SOI-ID spatial weight matrix instead uses Sphere of Influence contiguity with inverse-distance weighting before row-standardization. Sphere of Influence contiguity is more restrictive than Delaunay Triangulation contiguity, containing 18 undirected links compared with 22 under Delaunay, while retaining substantial overlap with the neighborhood structure of the benchmark spatial weight matrix (Jaccard similarity = 0.818). Finally, the K2-ID spatial weight matrix combines 2-nearest-neighbors contiguity with inverse-distance weighting before row-standardization. With 14 undirected links and a Jaccard similarity of 0.636 with Delaunay,

2-nearest-neighbors contiguity represents the largest change in neighborhood structure relative to the benchmark among the retained alternatives, while K2-ID additionally allows us to examine sensitivity to a fixed-neighbor structure.

Taken together, DT-ID² provides robustness to alternative distance-based weighting schemes while holding the benchmark neighborhood structure fixed, whereas SOI-ID and K2-ID provide robustness to alternative neighborhood structures combined with distance-based weighting. These alternative spatial weight matrices therefore allow us to examine whether the benchmark results depend on the use of a distance-based weighting scheme or on the underlying neighborhood structure.

Appendix B. Thematic maps of control variables

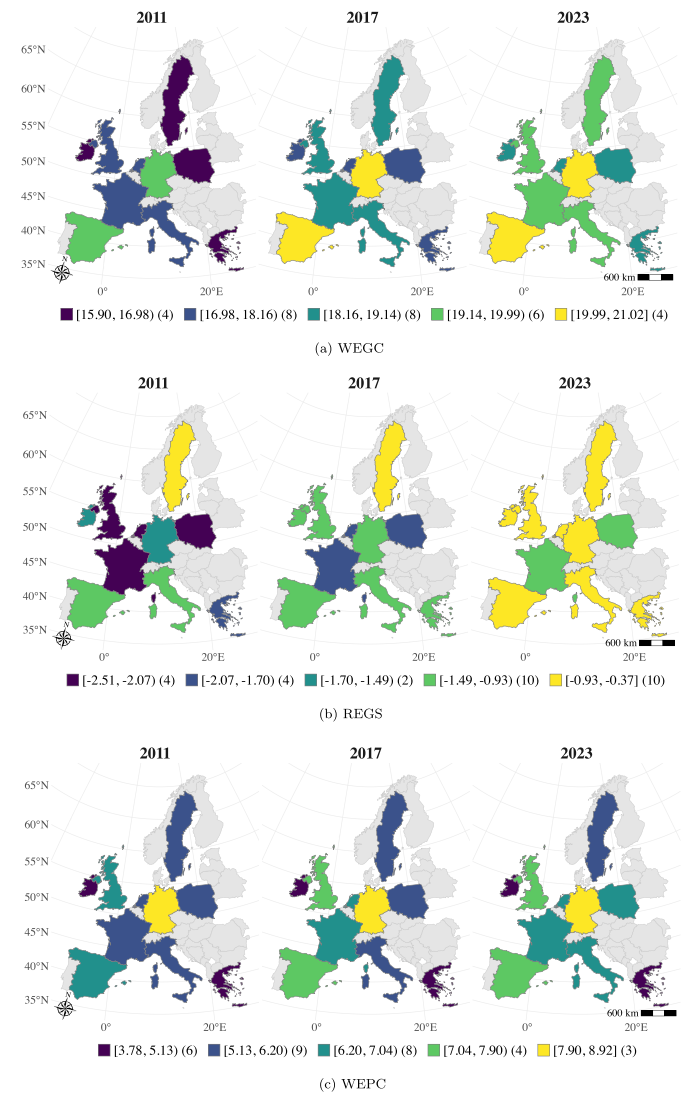


Fig. B.5. Thematic maps of control variables.

Appendix C. Robustness to alternative spatial weight matrices

To assess whether the results from the preferred spatial panel model, the SDM with two-way fixed effects, are sensitive to the spatial weight matrix specification, we re-estimate the model using the three alternative spatial weight matrices described in Appendix A. Specifically, we compare the benchmark results based on DT (SDM¹) with the results based on DT-ID² (SDM²), SOI-ID (SDM³), and K2-ID (SDM⁴).

Table C.5
SDM robustness to alternative spatial weight matrices.

All SDM Models:					
	Impact	SDM ¹	SDM ²	SDM ³	SDM ⁴
GDP	Direct	−0.86***	−0.79***	−0.63**	−0.61*
	Indirect	−2.25***	−3.02***	−2.83***	−1.36*
	Total	−3.12***	−3.81***	−3.46***	−1.97***
HDI	Direct	10.80***	11.07***	9.82***	8.73***
	Indirect	6.39	13.83***	17.02***	6.86*
	Total	17.19*	24.90***	26.85***	15.59***
GHG	Direct	0.82**	0.43	0.67**	0.89*
	Indirect	1.89**	1.98	1.33	1.45
	Total	2.71**	2.41*	2.00	2.34*
GRI	Direct	−2.50***	−1.39	−2.54**	−0.32
	Indirect	−6.22***	−6.45***	−3.19**	−3.77**
	Total	−8.72***	−7.85***	−5.72***	−4.08***
WEGC	Direct	−0.70***	−0.63***	−0.56***	−0.44***
	Indirect	−1.33***	−1.10**	−0.95***	−0.76*
	Total	−2.03***	−1.73***	−1.51***	−1.20**
REGS	Direct	0.59***	0.46***	0.48***	0.45***
	Indirect	0.70**	0.92**	0.61**	0.62**
	Total	1.29***	1.39**	1.09**	1.07**
WEPC	Direct	−2.81***	−2.25***	−1.93***	−1.78***
	Indirect	−3.28***	−3.04***	−1.22	−1.61***
	Total	−6.09***	−5.29***	−3.16***	−3.39***
ρ		−0.47***	−0.14**	−0.22***	−0.16*
R_w^2		0.86	0.86	0.88 [†]	0.87
R_b^2		0.01	0.01	0.02	0.10 [†]
R_o^2		0.16	0.20 [†]	0.18	0.19
LL		99.6	96.9	101.1 [†]	87.9
AIC		−173.2	−167.8	−176.3 [†]	−149.8
BIC		−135.9	−130.5	−139.0 [†]	−112.6

Notes: SDM¹–SDM⁴ use DT (benchmark), DT-ID², SOI-ID, and K2-ID, respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The corresponding direct, indirect, and total impacts are reported in Table C.5.

The results indicate substantial robustness of the main findings to alternative spatial weight matrices. For all four core explanatory variables, the signs of the direct, indirect, and total impacts remain unchanged relative to the benchmark results: the impacts of GDP and GRI remain negative, whereas those of HDI and GHG remain positive. The statistical significance of these impacts is also largely preserved. For GDP, all three impacts remain significant under all three alternative spatial weight matrices. For HDI, the direct and total impacts remain significant, while the insignificant indirect impact in the benchmark results becomes significant under all three alternatives. For GRI, the indirect and total impacts remain significant, whereas the direct impact is insignificant under SDM² and SDM⁴. However, the statistical significance of the GHG impacts is comparatively less robust: the indirect impact is insignificant under all three alternatives, whereas the direct and total impacts are insignificant only under SDM² and SDM³, respectively.

The results for the control variables are similarly stable. For WEGC and REGS, the direct, indirect, and total impacts retain their signs and remain statistically significant under all three alternative spatial weight matrices. For WEPC, the direct and total impacts also remain negative and statistically significant, while the indirect impact is insignificant only under SDM³. The estimated spatial autoregressive parameter ρ also remains negative and statistically significant under all three alternatives. Overall, although the magnitudes and statistical significance of some direct and indirect impacts vary across the alternative spatial weight matrices, the signs and statistical significance of the total impacts underlying the main conclusions are largely preserved. The benchmark findings therefore do not appear to depend on the specification of the spatial weight matrix.

Data availability

Replication data and source code associated with this article are available at Mendeley Data: <https://doi.org/10.17632/mzpz22x58x.4> (Kara and Acaroğlu, 2026).

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