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Regional drivers of industrial decarbonisation: a spatial econometric analysis of 238 EU regions between 2008 and 2020

Chiara Vagnini[a], Leticia Canal Vieira[a], Mariolina Longo[a] and Matteo Mura[a]

ABSTRACT
The European context of socio-economic integration and physical proximity likely plays an essential role in explaining the decarbonisation outcomes of industrial sectors. However, there is hardly any spatial regional analysis on CO_2 emissions drivers in European countries. This study investigates the role of geographical space and regional determinants in industrial decarbonisation by analysing how socio-economic drivers and their interregional relationships impact industrial carbon emissions in European regions. We employ a spatial panel data econometric model to a novel panel dataset comprising 13 years (2008–20) of carbon emissions from hard-to-abate industrial sectors from 238 NUTS-2 regions across 27 European Union countries. Results indicate the presence of endogenous spatial interactions and high-time persistence between CO_2-eq emissions in European Union regions. As such, industrial carbon emissions of regions follow similar patterns to their neighbours, supporting the evolutionary economic geography and growth theory assumptions of the spatial interaction of carbon emissions between regions. Furthermore, the use of a spatial econometric model illustrates the negative direct and spillover effects that higher levels of education and regional investment in research and development have on industrial CO_2-eq emissions.

KEYWORDS
carbon emissions; economic geography; European Union regions; panel data; spatial autoregressive (SAR) model; spatial spillover effects

JEL C23, O25, Q56, R11
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1. INTRODUCTION

Carbon emissions have become a global issue. They are the primary driver of climate change and their alarming atmospheric concentrations threaten the future of life on this planet (Intergovernmental Panel on Climate Change (IPCC), 2021). Reducing carbon emissions is particularly critical for the European Union (EU), one of the world's largest CO_2 emitters, along with China, the United States, India, Russia and Japan.

The EU has gained international recognition in recent decades for its leadership in decarbonisation efforts (Olivier & Del Lo, 2022). European policies have focused on emissions from fossil fuels and industrial processes that account for 78% of the overall increase in greenhouse gas emissions since 1970. Seeking to incentivise companies to reduce their emissions and facilitate a transition to a low-carbon economy, the EU established the world's first international emissions trading system (ETS) in 2005. The European Commission has also devised various policy instruments to promote the use of energy-efficient technologies and practices in the industrial sector (Vieira et al., 2022). As a result, several European countries have implemented policies to encourage the use of renewable energy (Olivier & Del Lo, 2022), such as feed-in tariffs, tax incentives and grants. In 2021, the EU reinforced its climate commitment through substantial investments in the Green Deal. This growth strategy aims to make Europe the first carbon-neutral continent by 2050 and requires a 55% reduction in greenhouse gas emissions by 2030 and an 80–95% reduction by 2050 compared with 1990 levels (IPCC, 2021). Although EU emissions fell by 5% in the last four years and continue in a downward trend, significant reductions are still required to achieve the net-zero objective (Crippa et al., 2022). Decarbonising energy-intensive industries is especially critical to this goal (Vieira et al., 2021).

Energy-intensive industries are deeply connected with their territories, which means that industrial outcomes are impacted by regional characteristics and dynamics. Regional data can help reveal the complete – and often complex – picture of decarbonisation drivers in industrial

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sectors, including the role of local dynamics. However, previous econometric studies have largely abstained from using regional data – a gap this article seeks to address. The significant variation in CO_2 emissions between different regions can be obscured by national figures, thus reinforcing the need to consider regional data (Mura et al., 2021; 2023). Such an analysis also needs to weigh a second aspect that is often neglected by econometric studies: the existence of spatial dependency among carbon emissions trajectories.

Indeed, despite the remarkable surge in academic research on the subject of CO_2 emissions drivers, most studies have ignored the importance of the spatial dimension. The existing literature has almost exclusively focused on studies at the country level using linear models (the only exceptions are the United States and China); there are hardly any spatial regional analyses on CO_2 emissions drivers for European countries (Balado-Naves et al., 2018). However, the physical proximity of locations is likely crucial for CO_2 emissions, as spatial spillovers can occur due to the underlying integration of economies (You & Lv, 2018). In the European context of socio-economic integration – which encompasses interregional trade, capital flows, migratory movements, and technology- and knowledge-transfer processes – geographical location and spatial connectivity are likely relevant for a decarbonisation process (Rios, 2017). In recent years, a growing body of studies has shown that CO_2 emissions drivers could be found not only within the region's administrative borders, but also in the dynamics of neighbouring areas (You & Lv, 2018). This regional integration also likely plays an important role in explaining the CO_2 emissions outcomes of industrial sectors. The transfer of cleaner technologies, distinct regulation settings that stimulate transboundary pollution flows, or the imitation of development models are examples of regional dynamics that can affect industrial carbon emissions (Rios & Gianmoena, 2018).

This study explores the role of geographical space and regional determinants in industrial decarbonisation. To that end, we analysed how socio-economic drivers and their interregional relationships impact industrial carbon emissions in European regions. We used a novel panel dataset comprising 13 years (2008–20) of carbon emissions from hard-to-abate industrial sectors in 238 NUTS-2 regions from 27 EU countries. The existence of spatial dependence for the carbon emissions of the aforementioned sectors justifies using a spatial panel econometric model to perform spatial lags on our dependent variable. We then elaborated a spatial panel econometric model with a range of drivers to investigate their direct effects (on regions' industrial CO_2-eq emissions) and indirect effects (in terms of spatial spillovers on the industrial CO_2-eq emissions of neighbouring regions). The proposed drivers were gross domestic product (GDP), education, service sector productive specialisation, and research and development (R&D) expenditures.

This study has three main contributions. First, using a spatial econometric model, we verify the presence of endogenous spatial interactions between CO_2-eq emissions in EU regions. As such, spatial effects are a relevant factor in the observed variability of CO_2-eq emissions: industrial carbon emissions from one region are impacted by neighbouring regions' dynamics. Second, we provide new insights into the direct and spillover effects of socio-economic drivers on regional CO_2 industrial emissions. The development of regional knowledge (i.e., education) and innovation (i.e., R&D expenditures), potentially leads to the creation and adoption of cleaner and more efficient industrial practices and technologies in heavy industries. Third, we contribute to evolutionary economic geography and growth theories by providing evidence of spatial interaction of carbon emissions among regions.

2. THEORETICAL FRAMEWORK

2.1. The role of space in industrial decarbonisation

Evolutionary economic geography, New Economic Geography and economic growth theories recognise the contribution of space in understanding why economic activities agglomerate and sustainability transitions unfold faster in certain locations than others (Hansen & Coenen, 2015; Rios & Gianmoena, 2018). These theories conceptualise physical space as the geographical distribution of organisational routines (Nelson & Winter, 1982), which tend to cluster in regions endowed with abundant natural resources, favourable socio-political and technological factors, robust infrastructure, supportive formal and informal institutions, strategic urban and regional planning, and shared cultural visions (Le Gallo et al., 2003; Boschma et al., 2017; Hansen & Coenen, 2015). Thus, firms tend to agglomerate in particular regions: not only to leverage knowledge-generating activities and the resulting spillovers (Duranton & Puga, 2005), but also to capitalise on the best labour pools and the most favourable institutional conditions (Storper, 1997). In other words, a company's choice of place is linked to the concentration of other businesses in the area – a self-reinforcing process.

Evolutionary economic geography seeks to unravel the factors that enable the emergence of an industrial growth pathway and their links to the regional context (Boschma et al., 2017). It emphasises how assets, skills, connections, and local competencies shape present and future industrial dynamics (Baumgartinger-Seiringer et al., 2022). The literature identifies path dependency, that is, historical contingencies and current state, as a significant determinant of an industrial growth pathway in a certain region (Martin & Sunley, 2006). For instance, the dependence of industrial pathways on their regional context may explain the uneven distribution of green activities and why only certain regions undergo a transition towards sustainability (Antonioli et al., 2016). Place dependency can trap firms in regional–technological specialisation regimes that are environmentally harmful and impede the shift into diversification practices with better environmental outcomes (Boschma et al., 2017). Place specificity can also delay the industrial adoption of environmental practices when regions are not able to design successful environmental policies (Hansen & Coenen, 2015). As such, the place is a relevant factor in understanding what fosters industries to decarbonise and what drives interregional differences (Santoalha & Boschma, 2021). We recognise the importance of space in understanding economic growth mechanism and green transitions, as suggested by existing theory. For this reason, this study seeks to respond to calls for advancing the development of generalisable knowledge about place specificity and how it can impact the transition to low-carbon economies (Santoalha & Boschma, 2021).

Attention to the role of regional characteristics in sustainability transitions literature is becoming increasingly important (Coenen et al., 2021). Regional capabilities are recognised to play a key role and low-carbon technologies are expected to develop more easily in regions with capabilities related to those technologies (Santoalha & Boschma, 2021). Studies have demonstrated how technological relatedness of the regional knowledge base increases regional diversification into cleantech (Tanner, 2016; van den Berge et al., 2020). Our study takes into consideration the role regional capabilities can play in industrial low-carbon transitions; however, it also considers that regions do not exist in a vacuum. Particularly in the European context, the interconnection among regions might mean that capabilities present in neighbours can produce spillover effects that affect other regions decarbonisation. Together with the analysis of place dependency in fostering green transitions, we also draw from the evolutionary economic geography emphasis on how spatial proximity between regions can shape interregional economic activities linkages which may also reflect on sustainability transitions (Moreno & Ocampo-Corrales, 2022). Linkages across regions have been marginally explored by transition studies, and those might play a relevant role for industrial low-carbon transition. Geographical proximity might influence positive development pathways (industrial, economic or technological) due to the exchange of tacit knowledge through transfer mechanisms such as inter-firm collaborations, professional networks and labour mobility (Boschma & Frenken, 2006). However, this is not the norm: positive trajectories in one region can be intertwined with negative trajectories in other regions due to spatial divisions of economic activities (Blažek et al., 2020). Differences in environmental standards or industry incentives can reinforce a division of specific industrial activities across regions, which could result in transboundary pollution flows (Rios & Gianmoena, 2018). We content that such division could result in certain regions concentrating polluting activities that might be linked to economic activities from neighbouring regions.

2.2 . Drivers of industrial CO_2 emissions

In the following, we will examine some of the key regional development drivers that can impact industrial decarbonisation, but for which there is no consensus in the literature regarding their effects.

Our choice of variables, namely GDP, education, service sector productive specialisation and R&D expenditures, collectively aim to capture a holistic representation of the socio-economic regional environment and ecosystem. By examining these variables and their interconnected roles, we seek to comprehensively understand the economic, innovative, educational and sectoral aspects that contribute to or hinder the transition toward sustainable industrial practices.

We reviewed studies concerning spatial and non-spatial analyses, but exclusively focused on absolute CO_2 emissions – rather than carbon intensity. Studies cover the European context and other geographical locations. This choice was motivated by the limited number of studies interrogating the phenomena in the European context and, more specifically, adopting regions as a unit of analysis.

Economic growth and development are considered predominant drivers of industrial carbon emissions. Scholars have taken contrasting positions on the impact of GDP on industrial CO_2 emissions. On one hand, both country- and region-level studies show that higher income leads to greater CO_2 emissions (Jaunky, 2011; You & Lv, 2018). Economic growth leads to greater consumption, and thereby production, which would seem to produce higher levels of industrial emissions. However, other studies have identified that an increase in GDP is associated with a decrease in emissions (Chen et al., 2018; Li et al., 2020). Studies on low-carbon transitions support the idea that European regions with higher economic development have greater access to resources, which can facilitate the development of technological alternatives or a low-carbon economy (Moreno & Ocampo-Corrales, 2022; Olivier & Del Lo, 2022). This, in turn, can positively impact the decarbonisation process of industries. Regions with higher GDP levels also tend to have policy agendas with an amplified focus on environmental protection. Therefore, industrial sectors are decarbonised by implementing policies and initiatives, such as carbon pricing mechanisms, energy efficiency standards, renewable energy targets, and sustainable production and consumption practices (Baiardi & Soana, 2023).

The environmental Kuznets curve (EKC) hypothesis is one explanation for the causal nexus between CO_2 emissions and economic growth (Grossman & Krueger, 1995). It suggests that the relationship between these two variables resembles an inverted 'U'-curve: environmental degradation rises during the early phases of economic growth, but then diminishes once a certain level of development is achieved (Ajmi et al., 2015). Such phenomena might be explained by a higher availability of financial resources that allow the investment in the infrastructure necessary to assist in industrial development toward low-carbon models (Blažek et al., 2020). Recently, both non-spatial and spatial econometrics studies have provided country- and region-level evidence for a robust, long-run, inverted 'U'-shaped relationship between CO_2 emissions and economic development (Balado-Naves et al., 2018; Nan et al., 2022; You & Lv, 2018). However, other studies contradict the inverted 'U'-shape of the EKC by finding either a 'U'-shaped relationship (Begum et al., 2015; Lantz & Feng, 2006), an 'N'-shaped EKC (Ajmi et al., 2015; Hossain et al., 2023; Kang et al., 2016), or a non-significance in the EKC pattern (Akbostancı et al., 2009; Coondoo & Dinda, 2008; He & Richard, 2010).

Recent studies also recognise the influence of non-economic factors on industrial CO_2 emissions. In particular, one stream of literature has posited that the level of education is an important driver of carbon emissions: some studies have reported a negative effect, while others have shown a positive effect. According to the first group, higher education levels are expected to alleviate CO_2 emissions due to facilitating the development and adoption of new technologies, practices and policies that are more energy-efficient, sustainable and less polluting (Li & Ullah, 2022; Liang et al., 2019; Zhao & Sun, 2022). In addition, some studies claim that higher education levels are associated with greater awareness of and concern for the environment (Zafar et al., 2020). A common finding of studies examining the emergence of green technologies is that they rely on a rich knowledge base drawing from fields both related and unrelated to these technologies (Santoalha et al., 2021). Therefore, individuals with higher levels of education are more likely to possess the skills and knowledge necessary to address environmental challenges. Conversely, another group of studies reports that education is a stimulant of environmental degradation (e.g., Zafar et al., 2022; Zhang et al., 2022). They argue that higher levels of education can lead to higher income and purchasing power for individuals, which can result in greater access to resource-intensive lifestyles (Zhang et al., 2022).

Empirical studies have also tested if the expansion of the service sector could impact industrial CO_2 emissions. According to Grossman and Krueger (1991), transforming the economic structure from energy-intensive industries into knowledge-intensive service sectors can improve environmental quality. The service sector – which includes services such as education, healthcare, finance and tourism – is generally considered to be less carbon-intensive than other sectors such as manufacturing and transportation. The service sector has been pointed out as having a lower reliance on fossil fuels and is often characterised by lower energy and material intensity (Kaika & Zervas, 2013). For instance, in recent years, BRICS countries (Brazil, Russia, India, China and South Africa) have actively promoted an economic structure shift towards the service industry, in the hopes of decoupling economic development from carbon emissions (Dudin et al., 2016). In contrast, some studies question this view and argue that the link between the service sector and carbon emissions reduction remains unclear. Al Mamun et al. (2014) and Zhang and Wang (2019) and Yang et al. (2019), for instance, explored the influences of service industry expansion on CO_2 emissions and found that the service sector output leads to an increase in carbon emissions. Zhang and Wang (2019) suggested that the service industry increases economic activity frequency and inefficiently uses resources, leading to greater waste and environmental degradation. Additionally, the development of the service industry has a strong 'pulling effect': although the direct CO_2 emissions from the service sector are relatively small, the increasing demand for services can result in greater resource inputs from non-service sectors, ultimately leading to more industrial CO_2 emissions.

Economic geography emphasises that innovation is what contributes to the emergence of new industrial paths in regions (Santoalha et al., 2021). The sustainability transitions literature also mentions that the existence of transformative change is the crucial element that allows the development and adoption of low-carbon technologies that are disruptive and radical (Santoalha & Boschma, 2021). As such, investments in R&D would be required not only to create new technological alternatives, but also to ensure technological acceptance and legitimation in socio-technical systems (Gibbs & Jensen, 2022). In recent years, there has been a particular focus on studies that aim to establish an empirical relationship between emissions and the innovation activity of economic actors, measured by R&D expenditures. The debate has gravitated towards whether investing in R&D can drive economic growth that is less polluting. Several studies have found that R&D expenditures facilitate industrial low-carbon transition by promoting the development and adoption of new technologies, practices, and policies that are more sustainable and less carbon-intensive (Cole et al., 2013; Qunfang & Huang, 2023; Shahbaz et al., 2018). Nevertheless, investments in R&D might also produce scale effects of higher growth and trade openness that result in increased CO_2 emissions (Churchill et al., 2019). Negative effects of R&D investments in industrial decarbonisation also link to an increase in the demand for highly polluting energy resources that generate more CO_2 emissions (Fernández et al., 2018).

Overall, there is little consensus on the direct effect of those drivers on industrial CO_2 emissions, and even fewer studies addressing their potential spillover effects. The existing controversies may reflect some endogeneity issues due to missing variables. Using different analytical methods and data from distinct geographical locations could alleviate some discrepancies in prior results (Rios & Gianmoena, 2018). By using a spatial model that assumes the existence of cross-regional interactions that can create spillover effects, our study hopes to advance the debate on the role of those drivers in industrial carbon emissions. As such, we seek to move the debate forward on the role regional drivers have in their own and nearby regions industrial decarbonisation.

3. DATA AND METHOD

Our empirical analysis utilised an original balanced panel dataset of 3094 observations. The dataset contains data on 238 regions belonging to 27 EU countries and comprises the period from 2008 to 2020. We retrieved the list of EU regions at the NUTS-2 level and used the 2016 NUTS classification by EUROSTAT (see Appendix

A in the supplemental data online for dataset construction). The list of regions included in the analysis is reported in Table A1 online.

The dependent variable *CO_2-eq emissions* was taken from the EU ETS database at the plant level and then aggregated at the NUTS-2 level. The independent and control variables were then taken from EUROSTAT at the NUTS-2 level. Table 1 contains summary statistics for 2020 (for a more comprehensive overview of the variables' descriptive statistics, see Table A2 online).

3.1. The model

In this section, we present the econometric model used to assess the drivers of industrial CO_2-eq emissions of EU regions. We first considered a non-spatial panel and then tested the possibility of extending this baseline model to include spatial interaction effects. We assumed that CO_2-eq emissions depend on select drivers according to the following relationship:

$$y_{it} = f\,(X_{it}) \tag{1}$$

where y_{it} is CO_2 emissions for region $i = 1, \ldots, N$ in year $t = 1, \ldots, T$; and X_{it} is the vector of the explanatory variables.

From equation (1), we can write the fixed-effect specification as follows:

$$y_{it} = \beta X_{it} + \eta_{it} \tag{2}$$

with:

$$\eta_{it} = \alpha_i + \varepsilon_{it} \tag{3}$$

where the α_i parameter is the fixed effects of the region i, which is assumed to be $INN(0; \sigma_\alpha^2)$; it captures unobserved heterogeneity across individuals that is fixed over time. β is the vector of parameters associated with the explanatory variable vector X_{it}.

The second step involves examining the joint significance of individual fixed effects and time-period fixed effects through the likelihood ratio (LR) tests. However, equation (2) does not consider the potential for spatial dependence in the values of CO_2-eq emissions. Interactions between regions can result in spatial autocorrelation, which, if ignored, can violate the assumption of error independence. The exclusion of spatial dependence in an econometric analysis when variables are spatially correlated would lead to bias, as pointed out by Anselin (1988) and Anselin et al. (2013). Therefore, we tested for the presence of spatial autocorrelation between the observation units. The cross-section dependence (CD) test advanced by Pesaran (2004) is very powerful against all forms of spatial dependence, but it does not allow one to discriminate between the two possible forms of autocorrelation (Anselin & Florax, 1995). For this reason, we used two Lagrange multiplier (LM) tests and their robust counterparts (Anselin, 1988; Anselin et al., 1996), which allow one to test the presence of an autoregressive spatial lag variable (LMlag and RLMlag) and a spatial autocorrelation of errors (LMerr and RLMerr).

These tests require the creation of a spatial weights matrix W, which is a $n \times n$ matrix where the spatial weights $w_{ij} = 1$ if regions i and j are neighbours, and 0 otherwise. In most of the cases, the binary 0–1 weights are row-standardised, that is, divided by the row sum. As a result, each row sum of the row-standardised weights equals 1, and the sum of all the weights, $\sum_i \sum_j w_{ij}$, equals the number of observations n. There are different spatial weight matrices available, and the choice of matrix is pivotal considering the different results each can yield (Anselin, 1988).

In this study, we used a 10-nearest neighbours (10nn) spatial weight matrix, calculated from the inverse squared distance between region centroids:

$$\begin{cases} w_{ij}(k) = 0 \text{ if } i = j, \quad \forall k \\ w_{ij}(k) = 1 \text{ if } d_{ij} \leq d_i(k) \\ w_{ij}(k) = 0 \text{ if } d_{ij} > d_i(k) \end{cases} \quad \text{and} \quad w_{ij}(k) = \frac{1}{d_{ij}^2} \tag{4}$$

where d_{ij} is the great circle distance between centroids of regions i and j; and $d_i(k)$ is a critical cut-off distance defined for each region i. More precisely, $d_i(k)$ is the kth order smallest distance between regions i and j such that each region i has exactly k neighbours. This matrix is preferred over the simple contiguity matrix often used in US and Chinese studies for several reasons. Compared with the United States and China, the sample of European regions is less compact, with an average of five to six contiguous neighbours per region. Our choice of 10nn yields a ring around each region of approximately the first- and second-order contiguous regions, as well as connects some islands such as Sicilia, Sardegna and Baleares to continental Europe (Gallo & Ertur, 2005). We chose the inverse-squared distance feature to avoid spurious neighbouring relations, because it assumes that the local influence of a region on its neighbours decays with the growing distance. Furthermore, the matrix was normalised according to row standardisation to interpret the spatial spillover effects as an average of all neighbouring regions.

In a panel data framework, W requires the following transformation:

$$W = I_n \otimes W \tag{5}$$

where I_t is the identity matrix.

After establishing a significant spatial autocorrelation between regions, we initiated the most common spatial econometrics models: the simultaneous autoregressive (SAR) and spatial error model (SEM) (Anselin, 1988). They differ in the way the spatial dependence is entered into the regression equation. The SAR assumes that the spatial dependence exists in the dependent variable: the value of the dependent variable observed at a particular region is partially determined by a spatially weighted average of neighbouring dependent variables. The SEM attributes the spatial interaction in the error terms: here, regional interaction effects are caused by the omitted variables that affect both the local and neighbouring regions.

Table 1. Variables summary statistics, 2020.

Variable	Abbreviation	Mean	SD	Minimum	Maximum
Carbon dioxide equivalent emissions (tons)	CO_2	5,127,432.38	6,947,923.92	1763.00	54,016,639.00
Gross domestic product (€ millions)	*GDP*	56,229.54	69,064.53	1508.54	710,090.66
Education (%)	*Educ*	32.05	9.78	11.80	59.70
Service sector productive specialisation (*n*)	*Service*	0.96	0.13	0.47	1.28
Research and development expenditures with a two-year lag (€ millions)	*RDlag2*	1118.98	1868.37	10.60	15,918.81
Industrial sector productive specialisation (*n*)	*Industr*	1.06	0.44	0.21	3.17

Note: R&D, research and development.

They are expressed as follows:

$$SAR: y_{it} = a \sum_{i=0}^{N} w_{ij} y_{it} + \beta X_{it} + \mu_i + v_{it} \quad (6)$$

$$SEM: y_{it} = \beta X_{it} + s_i + \varphi_{it}$$
$$\varphi_{it} = \lambda \sum_{i=0}^{N} w_{ij} \varphi_{jt} + n_{it} \quad (7)$$
$$n_{it} \rightarrow N(0, \sigma_n^2)$$

where a is the spatial autoregressive parameters for the spatially lagged dependent variable, and λ is the spatial autoregressive parameter for spatially lagged error term. These parameters indicate the extent of spatial dependence. The parameters μ_i and s_i capture the unobserved individual effect for the SAR and SEM models, respectively. Thus, we assume that they represent the fixed effects. v_{it} and n_{it} are the error terms.

The spatial weight matrix incorporated in the spatial regression models can render the standard ordinary least squares (OLS) estimation biased or inefficient. To overcome these issues, we adopted the maximum likelihood estimation procedure.

Various diagnostic tests can help illuminate which spatial panel data model better suits the data. In this study, we based our choice of model on the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Lower AIC and BIC values indicate a better model fit.

As the spatial models (SAR or SEM) do not account for the time-persistence effect, we also employed the Wooldridge test to confirm the presence of serial correlation (Wooldridge, 2002). Additionally, we performed the one-dimensional conditional test for zero random region effects by Baltagi et al. (2007), which allows for both serial and spatial correlation. If these tests are not rejected, then we need to pursue a spatial model that can account for both spatial and serial correlation. We therefore will assume the presence of serial correlation in the remainder of the error term from the SAR and SEM models, following Olivier and Del Lo (2022). We will refer to these models as the SARsr and SEMsr models; in all of them we presumed that the error terms of equations (4) and (6) follow an autoregressive process of order 1:

$$SARsr: v_{it} = \omega v_{it-1} + e_t \quad (8)$$

$$SERsr: n_{it} = \omega n_{it-1} + r_t \quad (9)$$

where v_{it} and n_{it} are independent and identically distributed.

Notably, the presence of spatial correlation in the spatial regression models complicates the interpretation of the coefficients of the explanatory variables. The change of one variable not only affects the local CO_2 emissions, but also influences the CO_2 emissions of nearby provinces, which then creates a feedback loop. In other words, when a model features the spatial lags of the dependent variable and independent variables, the true total effect of an explanatory variable's unit change on a dependent variable does not accurately capture the marginal effect, such as in the standard regression models ($\hat{\beta}$); it also reflects the spatial connections and simultaneous feedback that pass through the dependency system. It is thus possible to identify three effects: direct, indirect and total effects (LeSage & Pace, 2008). In our study, the direct effect estimates the impact of changes in the independent variable(s) on CO_2-eq emissions in a particular region. The indirect effect represents the impact of changes in an independent variable of other locations on the local CO_2 emissions (spillover effect). The total effect is simply the sum of the direct and indirect effects.

Finally, we tested alternative spatial weights matrices (*k*nn = 15, 20, 25) to check the robustness of the estimation results.

3.2. The variables

In this section, we outline the dependent, independent and control variables employed in our empirical analyses. Our dependent variable is *CO_2-eq emissions*, measured as CO_2-equivalent emissions in tons. To procure primary data, we accessed the EU ETS database in 2020 and aggregated data at the 2016 NUTS-2 classification level to derive emissions values for ETS industries in the region.

The independent variables comprised the drivers for industrial CO_2 emissions described in the theoretical framework section, and data were retrieved from the EUROSTAT database at the 2016 NUTS-2 classification level. The first independent variable considered was *GDP* which indicates the outcome of production activities by resident producer units in millions of euros. *Education* was the second independent variable, measured as the percentage of population aged 25–64 years with a tertiary education. We adopted the International Standard Classification of Education (ISCED) and considered individuals at levels 5–8 as those with a tertiary education. *R&D expenditures* was the third independent variable, measured by gross domestic expenditure on R&D in millions of euros, with a two-year lag. The impact of R&D spending on the economy may not be immediate and it is common for empirical studies to incorporate a delay in this variable when examining the relationship between R&D spending and environmental impacts (Fernández et al., 2018; Garrone & Grilli, 2010). We followed this literature and adopted a two-year lag into the R&D expenditures variable in our model.[1] Finally, we integrated *service sector productive specialisation* as an additional independent variable. EUROSTAT provides a sectoral breakdown of economic indicators homogenised to NACE revision 2 classifications. Service sector productive specialisation contains the gross value added (GVA)[2] of the NACE revision 2 sectors Wholesale Retail and Trade (G–J), Finance and Business (K–N), and Non-market Services (O–U). The variable was calculated using the sector specialisation index (S index), a tool designed by the European Commission to assess a region's sectorial specialisation (Directorate-General for Enterprise and Industry (DGEI), 2011, pp. 39–42). This index compares the proportion of a given sector j in a specific region i with its representation within the entire EU, and it is calculated as follows:

$$S_{i,j} = \frac{\dfrac{GVA_{i,j}}{\sum_j GVA_{i,j}}}{\dfrac{GVA_{EU,j}}{\sum_j GVA_{EU,j}}} \quad (10)$$

Service sector productive specialisation represents the comparison between the proportion of value-added from NACE revision 2 sectors G–U to total GVA in a specific region and its representation within the entire EU. Values above (below) 1 signify specialisation (lack of specialisation) of the region in that sector, and the higher the value of the indicator, the higher the region's specialisation compared with the EU average.

In our analyses, we controlled for the regional industrial structure of the territories by introducing the *industrial sector productive specialisation* variable. Previous literature has established a positive relationship between industrial sector and carbon emissions, given that industrial activities are energy-intensive and a major source of these emissions (Liu et al., 2018; Nan et al., 2022; Shahnazi & Dehghan Shabani, 2019; Zhou et al., 2023). This variable was also calculated using the S index. It reflects the proportion of value-added from the Industrial (B–E) sector of the NACE revision 2 classification to total GVA in a specific region and its representation within the entire EU. Table A3 in Appendix A in the supplemental data online shows the correlation among the proposed variables.

4. RESULTS

Figure 1 displays the variation of industrial CO_2-eq emissions across the EU regions from 2008 to 2020 and highlights the different results. Among the 238 regions analysed, approximately 83% (197 regions) have decreased their emissions during this period. Conversely, about 17% (41 regions) have experienced increases in emissions, with seven regions presenting a growth higher than 50% compared with their 2008 levels.

Table 2 presents the results of the OLS, SAR and SEM models. OLS model (1) omits *industrial sector productive specialisation*, our control variable, while model (2) incorporates it. Table A3 in Appendix A in the supplemental data online demonstrates the strong correlation between the variables *service sector productive specialisation* and *industrial sector productive specialisation* ($r = -0.892$, $p < 0.01$). Also, Table A4 online shows high variance inflation factors (VIFs) associated with *service sector productive specialisation* (VIF = 7.466) and *industrial sector productive specialisation* (VIF = 6.907). These results suggest potential multicollinearity between these two variables. We prioritised the examination of service *sector productive specialisation* (our independent variable) over *industrial sector productive specialisation* (the control variable). Consequently, we focus on the results derived from model (1).[3]

Tables A5 and A6 in Appendix A in the supplemental data online show the results of the different non-spatial panel data models – pooling, individual fixed effects, time-period fixed effects and their combination. These analyses revealed the presence of spatial and serial dependencies in the data. Specifically, the Pesaran (CD) and LM tests indicate the existence of spatial interdependence, while the Wooldridge test confirms the presence of serial correlation. Further validation comes from the results of the one-dimensional conditional test, revealing the impact of both serial and spatial correlation on our model (without random effects) (see Table A5 online). These results suggest that to achieve a more accurate analysis, we need to use a spatial econometric model that considers both spatial and serial correlation. Following Oliver and Del Lo (2022), we will now comment on the models with spatial correlation (SAR and SEM) and direct readers to Table A7 online for the model estimations which also incorporate serial correlation (SARsr, SEMsr).

Table 2 shows similar results for the SAR and SEM models. The estimated coefficients associated with the spatially lagged (SAR model) were positive and statistically significant. The same can be said for the spatial error term coefficient of the SEM model. After comparing these models using AIC, BIC and log-likelihood selection criteria, we found that the SAR model performed the best. However, given the statistically significant spatial autocorrelation coefficient, the parameter estimates of the SAR

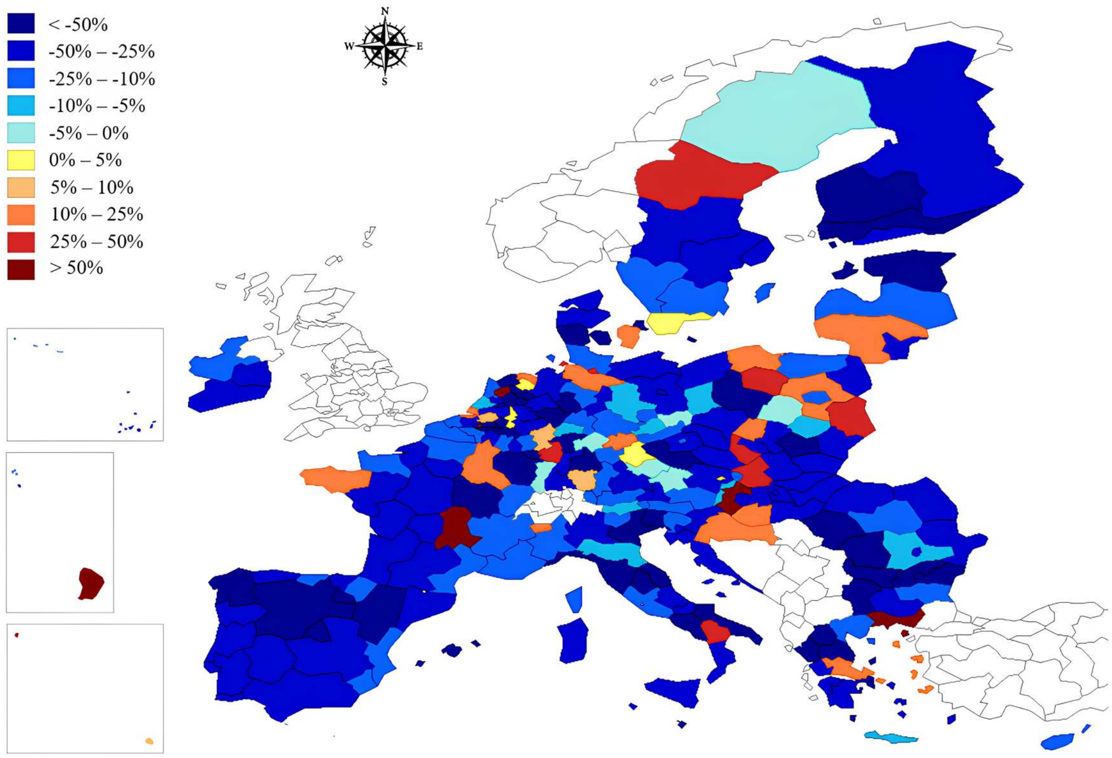

Figure 1. Percentage of industrial CO_2-eq emissions variation across European Union regions, 2008–20.

Table 2. Estimation results.

	OLS		SAR		SEM	
	(1)	(2)	(1)	(2)	(1)	(2)
α			0.0804***	0.0804***		
			(0.0264)	(0.0264)		
λ					0.0487*	0.0488*
					(0.0274)	(0.0274)
GDP	1.4675***	1.4708***	1.4240***	1.4229***	1.4460***	1.4457***
	(0.3779)	(0.3789)	(0.3619)	(0.3629)	(0.3658)	(0.3668)
GDP^2	−0.0776***	−0.0778***	−0.0751***	−0.0750***	−0.0772***	−0.0771***
	(0.0185)	(0.0186)	(0.0177)	(0.0178)	(0.0179)	(0.0180)
Educ	−0.4185***	−0.4180***	−0.3855***	−0.3857***	−0.4049***	−0.4050***
	(0.0376)	(0.0379)	(0.0368)	(0.0371)	(0.0369)	(0.0372)
Service	−0.7368***	−0.7542***	−0.6935***	−0.6878***	−0.7049***	−0.7033***
	(0.1317)	(0.1946)	(0.1263)	(0.1864)	(0.1272)	(0.1877)
RDlag2	−0.0126***	−0.0126***	−0.0120***	−0.0120***	−0.0122***	−0.0122***
	(0.0043)	(0.0043)	(0.0041)	(0.0041)	(0.0042)	(0.0042)
Industr		−0.0107		0.0035		0.0010
		(0.0876)		(0.0839)		(0.0844)
R^2	0.1013	0.1013				
AIC			−272.6113	−270.6131	−259.1642	−257.1609
BIC			−236.388	−228.3525	−216.9036	−208.8631
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. In model (1), the control variable is not taken into account, while model (2) integrates the control variable.
AIC, Akaike information criterion; BIC, Bayesian information criterion; FE, fixed effects.

model cannot be interpreted as marginal effects of the corresponding explanatory variables on the dependent variable, as in the case of non-spatial models. For this reason, Table 3 reports the direct and indirect effects of the independent variables to interpret the spatial spillover effects.

4.1. The spatial effect of CO_2-eq emissions

Table 2 shows that the spatial autocorrelation parameters associated with the spatial lag of CO_2-eq emissions are positive and statistically significant, no matter the econometric specifications considered ($\alpha = 0.080$, $\lambda = 0.049$, with $p_\alpha < 0.01$ and $p_\lambda < 0.1$). In short, we uncovered positive geographical spillover and confirmed that physical proximity increases or decreases carbon emissions. As such, neighbour regions follow similar emissions patterns: the higher (or lower) the CO_2-eq emissions of neighbouring regions, the higher (or lower) the CO_2-eq emissions for the focal region. The spatial dependence of carbon emissions can be attributed to the underlying integration of economies in the EU regions (Rios, 2017). This integration means that the production network of hard-to-abate industries relies on value chains that stretch across multiple regions or countries (de Bruyn et al., 2020). For instance, if a component used in producing goods from one region is manufactured in another region, it can create a spillover of emissions. As a result, a pollution transfer or leakage can occur where one region gains the economic benefits of a particular good, but the manufacturing emissions of this good are linked to another region. Granted, production networks may not be the only culprit: The spatial dependence of emissions might speak to competition or imitation effects. For instance, one region may seek to emulate neighbouring regions' industrialisation level and development patterns, even if that entails negative environmental consequences (Wang et al., 2018).

4.2. The direct and spillover effects of socio-economic variables on CO_2-eq emissions

In this section, we examine how socio-economic drivers and their interregional relationships impact industrial carbon emissions in EU regions. We discuss the direct effects of these variables on a region's emissions and their spillover effects in nearby regions. We specifically analysed GDP and its squared term, education, service sector productive specialisation, and R&D expenditures. Table 3 presents the results.

The first variable we analysed was GDP. We found that an increase in a given region's GDP has a positive direct effect on local CO_2-eq emissions ($\beta = 1.426$, $p < 0.01$) and a positive spillover effect in neighbouring regions ($\beta = 0.123$, $p < 0.05$). Specifically, a 1% increase in GDP is associated with a 1.43% increase in direct CO_2-eq emissions. One possible explanation is that economic growth often produces more industrialised regions. Obviously, industries dependent on fossil fuels will produce higher emissions as industrialisation increases. Additionally, wealthier populations tend to consume more goods and services, which can also increase hard-to-abate industries' activity. Considering the spillover effect, a 1% increase in adjacent regions' GDP can raise the neighbour region's carbon emissions by roughly 0.12%. As such, the spillover contributes to 8%[4] of GDP's total effect on CO_2-eq emissions, underscoring the impact of one region's economic activity on its neighbours' emissions.

Our analysis also included the squared GDP in the model to explore the existence of an inverted 'U'-shaped relationship between economic growth and industrial carbon emissions. We obtained negative and significant coefficients for the direct ($\beta = -0.075$, $p < 0.01$) and spillover effects ($\beta = -0.007$, $p < 0.05$), confirming the validity of an EKC relationship. Thus, there is a turning point after which economic growth has a negative effect on a region's industrial carbon emissions. Reaching this turning point also has a negative spillover effect on nearby regions that contributes to 8% of a region's total industrial emissions reduction.

Education also contributed to reducing the industrial carbon emissions of a given region ($\beta = -0.386$, $p < 0.001$) and had a negative spillover effect ($\beta = -0.033$, $p < 0.01$). Specifically, a 1% increase in education was

Table 3. Direct, indirect and total effects of the SAR model.

	Direct effects		Indirect effects		Total effects	
	(1)	(2)	(1)	(2)	(1)	(2)
GDP	1.4256***	1.4245***	0.1228**	0.1228**	1.5484***	1.5473***
	(0.3374)	(0.3863)	(0.0554)	(0.0519)	(0.3735)	(0.4207)
GDP^2	−0.0752***	−0.0751***	−0.0065**	−0.0065**	−0.0817***	−0.0816***
	(0.0164)	(0.0190)	(0.0028)	(0.0027)	(0.0182)	(0.0207)
Educ	−0.3860***	−0.3861***	−0.0333***	−0.0333***	−0.4192***	−0.4194***
	(0.0342)	(0.0377)	(0.0126)	(0.0116)	(0.0406)	(0.0429)
Service	−0.6943***	−0.6886***	−0.0598***	−0.0594**	−0.7541***	−0.7479***
	(0.1249)	(0.1806)	(0.0244)	(0.0256)	(0.1388)	(0.1965)
RDlag2	−0.0120***	−0.0120***	−0.0010**	−0.0010**	−0.0130***	−0.0130***
	(0.0040)	(0.0041)	(0.0005)	(0.0005)	(0.0044)	(0.0045)
Industr		0.0035		0.0003		0.0038
		(0.0849)		(0.0073)		(0.0918)

Note: Standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. In model (1), the control variable is not taken into account, while model (2) integrates the control variable.

associated with a 0.39% reduction in direct CO_2-eq emissions. Skilled labour and specialised knowledge are not only crucial for the operation of hard-to-abate industries, but can also contribute to optimising industrial practices and promoting cleaner technologies. In addition, higher levels of education might spur greater awareness about environmental issues, which might then inform people's political choices. This could lead to the election of policymakers who are more prone to implementing greener policies (Zafar et al., 2020) that target sustainability practices in hard-to-abate industries.

An increase in the service sector productive specialisation presented a negative and significant direct effect on industrial emissions ($\beta = -0.694$, $p < 0.01$). Thus, a 1% increase in the service sector productive specialisation was associated with a 0.69% decrease in regional industrial emissions. The spillover effects of the service sector productive specialisation were also negative, but did not achieve a significant level ($\beta = -0.060$, $p < 0.01$). Our finding aligns with the existing literature asserting that a transformation in economic structure from energy-intensive industries to knowledge-intensive service sectors can lead to improvements in environmental quality (Grossman & Krueger, 1991). The service sector, encompassing services such as education, healthcare, finance and tourism, is generally recognised as less carbon-intensive compared with sectors such as manufacturing and transportation, as it typically relies less on fossil fuels and exhibits lower energy and material intensity (Kaika & Zervas, 2013).

Investment in R&D is another factor that, together with education, contributes to reducing industrial carbon emissions. An increase in R&D investment had a negative and significant direct effect (with a lag of two years) in reducing a given region's industrial carbon emissions ($\beta = -0.012$, $p < 0.01$). Its spillover effect was negative and significant ($\beta = -0.001$, $p < 0.05$). In other words, every 1% increase in R&D expenditures was associated with a 0.01% drop in industrial carbon emissions of the same region two years later and a 0.001% drop in neighbouring regions. This result aligns with previous studies on the role of R&D in reducing carbon emissions (Cole et al., 2013; Qunfang & Huang, 2023).

4.3. Robustness checks

To offer a more robust and nuanced understanding of the spatial relationships and dynamics under investigation, we conducted a sensitivity analysis by considering the spatial weight matrices of the 15nn, 20nn and 25nn, calculated from the inverse squared distance between region centroids. The results are shown in Table A8 in Appendix A in the supplemental data online. The findings corroborated those obtained with the spatial weight matrix of the 10nn. The spatial lag coefficients were positive and highly significant, varying from 0.201*** (if we consider the 15-closest neighbours) to 0.213*** (20-closest neighbours), and 0.221*** (25-closest neighbours). These results confirm the CO_2-eq emissions are interdependent and considerably clustered. The results for the explanatory variables were qualitatively unchanged.

5. CONCLUSIONS

As societies seek to reduce their industrial emissions rapidly, the academic literature has scrutinised intensely the drivers of carbon emissions. Adding to this stream, this study explored the role of geographical space and regional determinants in industrial decarbonisation. Specifically, we analysed how socio-economic drivers and their interregional relationships impact industrial carbon emissions in European regions. The EU has attracted particular interest among academics because it remains one of the largest emitters in the world despite its international recognition for leadership in decarbonisation efforts. However, research has almost exclusively focused on studies at the country level and few studies have examined this issue through spatial econometric models. To address that gap, we conducted a spatial analysis using an original panel dataset composed of 238 regions from 27 EU countries for the period 2008–20. As such, we produced generalisable knowledge on the role of spatial proximity and regional characteristics in reducing heavy industries' carbon emissions.

Our study presents three contributions. First, it validates the endogenous spatial interactions between CO_2-eq emissions in EU regions for all the econometric specifications considered. In short, the industrial carbon emissions in a given region are shaped by the activities of neighbouring regions. Thus, the underlying integration of economies in EU regions likely results in carbon emissions spillovers. The spatial dependence of carbon emissions might also indicate competition or imitation effects that result in neighbouring regions with similar industrialisation and development patterns.

Second, using a spatial econometric model, we provide new insights into various drivers' direct effects on regional CO_2-eq industrial emissions and spillover effects. Our findings demonstrate that increased GDP results in higher levels of industrial emissions in regions and their neighbours, but only up to a certain threshold. This inverse-'U' pattern likely stems from the development of regional knowledge (i.e., education) and innovation (i.e., R&D expenditures), which leads to the creation and adoption of cleaner and more efficient industrial practices and technologies in heavy industries. Notably, having drivers linked to knowledge capacity (allowing for the development of low-carbon industrial activity) seems to be critical to decarbonisation. Additionally, replacing carbon-intensive industrial activity with service industries seems to hinder industrial emissions, facilitating decarbonisation outcomes. Granted, we recognise that EU regions vary considerable in their emissions reductions (from 10% to 50%). Thus, the relative impact of cleaner technologies and the service industry might become clearer at higher levels of mitigation.

Third, we contribute to evolutionary economic geography and growth theories. We confirmed previous results about the role of the analysed variables in shaping CO_2 emissions within the immediate geographical area, as well as generated new insights regarding the spillover effects on neighbouring regions.

These findings call for coherent policy-related instruments that consider direct and spillover effects. Given the existence of endogenous spatial interactions between carbon emissions in EU regions, policymakers need to focus their efforts on avoiding pollution transfers and achieving absolute emissions reductions. Each region has territorial specificities that require specific local policies; thus, coordinated policy instruments may be needed to prevent undesirable spillover effects. Regional governments can play a key role in mobilising resources, fostering innovation and facilitating the development of sustainable practices. Our findings suggest that coordinated investments in tertiary education and R&D expenditures may be promising starting points.

Of course, this paper contains some limitations that may inspire future research. First, our study collected data from the hard-to-abate industrial sectors. Expanding the scope to include data sources from other sectors (industrial or otherwise) could offer a more complete understanding of the obstacles and prospects facing our societies. Second, we only analysed four independent variables. Further research could employ additional variables in order to better represent the drivers of carbon emissions, such as institutional variables (e.g., institutional quality, regulations and standards) and those specifically linked to the industrial sectors (e.g., energy consumption, number of industrial facilities, employment, technological innovation, environmental-related practices). Third, the current study does not encompass data pertaining to imports and potential exports beyond the EU. In order to provide a more comprehensive analysis, future research should explore carbon emissions associated with international trade activities, placing a specific emphasis on imports from major contributors, notably China. Moreover, future studies could benefit from integrating endogenous and imported technologies into their analytical frameworks, as these play a crucial role in facilitating the transition towards cleaner structures and industries in Europe. Fourth, this study was centred on the regional level. Future research could refine the unit of analysis by shifting to a lower geographical scale, such as industrial hotspots, poles or hubs, or by concentrating on representative clusters. This would allow for the analysis of significant processes of industrial plant relocation and production fragmentation that have occurred in recent decades.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

NOTES

1. We also carried out robustness checks using different temporal delays ($t-1$, $t-2$ and $t-3$) and found no significant differences in the results.
2. Total GVA denotes the output value at basic prices less intermediate consumption valued at purchasers' prices for the secondary and tertiary sectors.
3. Tables A9 and A10 in Appendix A in the supplemental data online provide further details on the effect of *industrial sector productive specialisation* on carbon emissions when *service sector productive specialisation* is not considered.
4. To determine the spillover magnitude of a variable on its total effect in percentage, we calculated the product of the variable's spillover effect times 100 and divided the result by the variable's total effect; that is, for GDP: $(0.123 \times 100)/1.548 \approx 8\%$.

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