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Carbon emissions from European land transportation: A comprehensive analysis

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A R T I C L E I N F O

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A B S T R A C T

This study examines carbon emissions from European land transportation, considering spatial autocorrelation patterns. Using global and local Moran's *I* indices, we find evidence of positive spatial autocorrelation in the panel data of 26 European countries from 1995 to 2019. To adequately analyze the factors influencing transport emissions, we then employ the spatial Durbin model and integrate transport-specific regression models, extending the classic *STIRPAT* model. The regression models include parameters such as transport intensities, modal splits between road and rail, and infrastructure density. Understanding spatial patterns in transport emissions provides valuable insights for policymakers in developing more effective emissions reduction strategies. Our results emphasize the importance of close European cooperation due to significant spatial dependencies, urging reductions in transport intensities and a shift from road to rail services. Additionally, we identify a non-linear relationship between infrastructure development and carbon emissions, suggesting the existence of 'sustainability sweet spots' in future infrastructure planning.

1. Introduction

Carbon emissions are a major contributor to climate change, which brings severe weather events, rising sea levels, and other detrimental environmental impacts (Intergovernmental Panel on Climate Change, 2013; 2022). In 2019, global emissions were approximately 35 gigatons, an increase of 14 gigatons compared to 1990 levels (World Bank, 2022). Therefore, it is crucial to act promptly in order to reduce carbon emissions and address climate change, to sustain the environment and preserve the planet for future generations (Intergovernmental Panel on Climate Change, 2022). At the global level, legally binding treaties, such as the United Nations Framework Convention on Climate Change, the Kyoto Protocol, and the Paris Climate Agreement, take a regulatory approach to promoting sustainable development (United Nations, 1997; 2015). For example, signatories to the Paris Climate Agreement have committed to reducing or offsetting emissions in order to limit global warming to 1.5 degrees Celsius above pre-industrial levels, corresponding to the period between 1850 and 1900, and curb further irreversible climate change (United Nations, 2015).

The European Union (EU)[1] is a conglomerate of industrialized countries with relatively high carbon emissions (World Bank, 2022). Its member states have subscribed to particularly ambitious emissions reduction targets. For example, the European Green Deal, ratified by the European Commission in 2019, commits signatories to reducing emissions by at least 55% from 1990 levels by 2030,

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[1] We provide a detailed notation list in Table S1 in the Supplementary Material.

and to achieving climate neutrality, in terms of zero net greenhouse gas (GHG) emissions, by 2050 (EU Commission, 2019). In line with this, initiatives have already been launched across various industrial sectors in EU member countries (EU Commission, 2023). As illustrated in Fig. 1, total carbon emissions from the EU 27 countries declined between 1990 and 2019, with a more rapid reduction since 2010. This finding supports the validity of the environmental Kuznets curve (EKC) hypothesis that there is an inverted U-shaped relationship between economic growth and environmental pollution. Environmental pollution increases at the initial stage of economic development, but decreases with further economic development (Grossman and Krueger, 1991; Guo, 2021). Extant studies report that the EKC hypothesis holds true for many countries, including the US and EU member states (Dogan and Turkekul, 2016; Vasylieva et al., 2019).

However, the EU and its member states are falling short of achieving their sustainability targets. Fig. 1 highlights a discrepancy of 1.17 billion ton between actual emissions in 2019 and 2030 targets. Of particular concern is the transport sector, one of the EU's major sources of emissions, where reduction targets are being missed (Danielis et al., 2022). As shown in Fig. 2, the transport sector is the only sector in the EU where emissions increased from 1990 to 2019. In 2019, the transport sector's emissions were over 25% higher than the 1990 levels, resulting in the transport sector's share of total EU carbon emissions reaching nearly 30% (Ritchie et al., 2020).

Land transportation significantly contributes to transport-related carbon emissions (TCE) in the EU (EU Parliament, 2019). Especially in light of the European Green Deal, policymakers and other transportation stakeholders must urgently address the carbon footprint from land transportation (Siskos et al., 2018). While the EU has already implemented measures to reduce TCE, such as the mandate for new passenger cars to be zero-emission vehicles by 2035 (EU Commission, 2022a), current reduction efforts seem to fall short of meeting the long-term sustainability targets (Robaina and Neves, 2021). For instance, the slow adoption of zero-emissions vehicles and challenges in vehicle availability, charging infrastructure, and fueling infrastructure hinder progress (Ragon and Rodríguez, 2022).

Considering the importance of reducing emissions from land transportation (Robaina and Neves, 2021), our empirical research aims to enhance the understanding of the factors that influence emissions from European land transportation. This paper differs from previous studies as it considers (potential) spatial autocorrelation patterns in the TCE. Spatial autocorrelation implies that a nation's transport emissions are influenced not only by local factors, but also by factors of neighboring countries. To our knowledge, spatial autocorrelation in transport emissions is under-explored in the literature, particularly in the context of European land transportation. The limited body of literature on this topic largely focuses on China, such as Yu et al. (2013) and Yang et al. (2019). We aim to address this research gap with respect to the European context and pursue two primary research objectives. One objective is to provide empirical evidence of spatial patterns in carbon emissions from European land transportation. The other objective is to refine our understanding of factors that influence carbon emissions from European land transportation by taking spatial autocorrelation into account in the empirical analysis of these influencing factors. Neglecting to account for spatial pattern would lead to biased estimates and potentially misleading findings (Yang et al., 2019).

Our empirical analyses are based on panel data of 26 European countries, i.e., the current 27 EU countries, minus Malta and Cyprus, plus the United Kingdom (UK). The data spans from 1995 to 2019. Our methodology is informed by previous studies, including those conducted by Yu et al. (2013) and Yang et al. (2019). As proposed by Anselin (1988) and Anselin and Florax (1995), we use global and local Moran's *I* indices to examine spatial autocorrelation patterns in carbon emissions from European land transportation. To account for spatial autocorrelation in the empirical analysis of the influencing factors, we utilize the well-established spatial Durbin model (LeSage and Pace, 2008; Elhorst 2012; 2014) and integrate transport-specific regression models based on the classic *STIRPAT* model proposed by Dietz and Rosa (1997). After reviewing the literature on relevant influencing factors in land transportation, such as Jennings et al. (2013) and Andrés and Padilla (2018), we have formulated two types of transport-specific regression models to investigate different aspects of the land transportation. The first is the transport activity model, which mainly focuses on transport intensities and modal splits. The second is the transport infrastructure model, which mainly focuses on infrastructure. Further details on the methodologies can be found in Fig. S1 in the Supplementary Material.

We contribute to the literature in the following respects. We are the first to find evidence of positive spatial autocorrelation in carbon emissions from European land transportation. Our findings reveal that carbon emissions tend to cluster geographically and provide valuable insights for designing location-specific strategies to reduce TCE. Additionally, we are the first to employ a spatial econometric model to analyze factors that influence carbon emission from European land transportation. The use of a spatial econometric model is necessary due to the spatial autocorrelation feature of TCE. Different from existing studies, our approach provides a more nuanced perspective on transport emissions, offering insights into how a country's transport emissions are influenced by both internal factors (direct effects) and factors of neighboring countries (indirect, spillover effects).

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 introduces the data and methodologies employed. Section 4 presents the empirical results. Section 5 discusses the findings and policy implications. Section 6 summarizes the paper. Section 7 describes potential limitations and makes suggestions for further research.

2. Literature review

The environmental impact of transportation has been broadly studied. Part of this literature aims to understand the factors that influence transport emissions, whereby many studies rely on the *IPAT* identity that was introduced by Ehrlich and Holdren (1971,

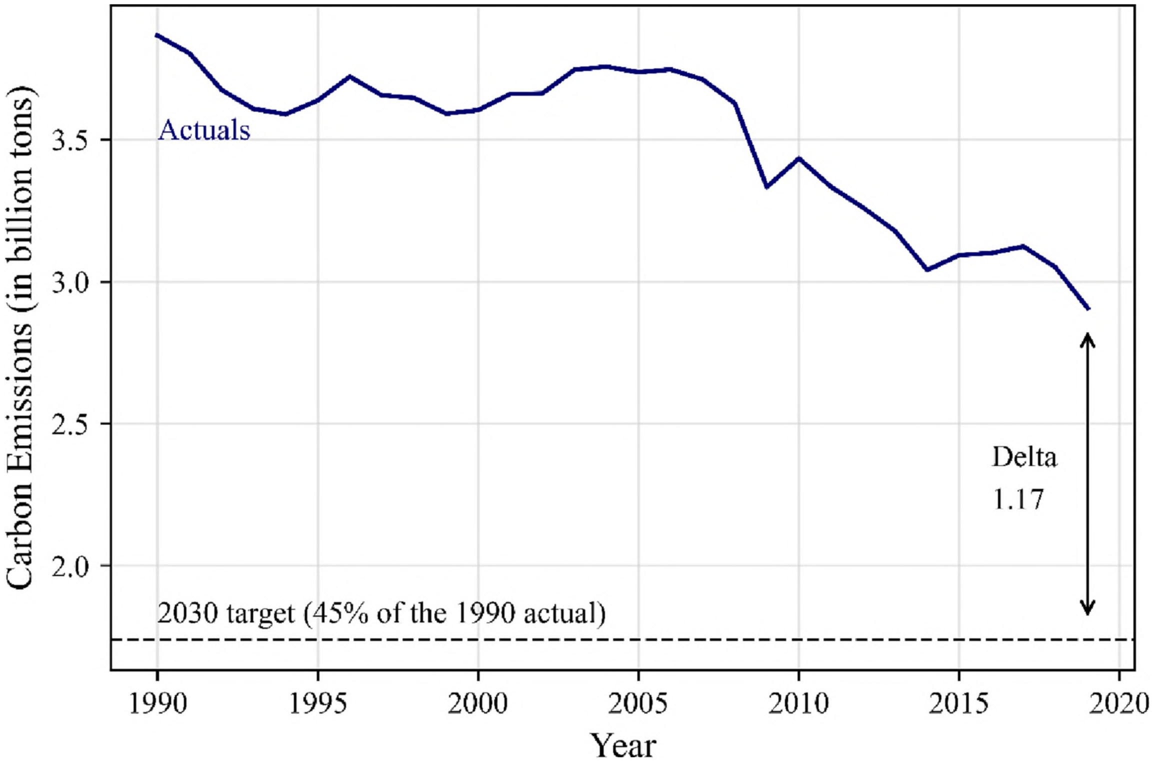

Fig. 1. Evolution of carbon emissions (EU 27 countries, 1990–2019). Note: The 2030 target represented by the horizontal dashed line is calculated as 45% of actual CE in 1990, which is the 55% reduction target in the European Green Deal. Data drawn from Ritchie et al. (2020). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

1972). This identity expresses the environmental impact (I) as the product of population (P), affluence (A) and technology (T). In addition, researchers have developed expanded versions of the *IPAT* identity, such as the Kaya (1989) identity and the ASIF methodology (International Energy Agency, 1997).[2]

A large body of research has emerged around the *IPAT* identity and its variations, mostly based on time-series data at a national level and applying various decomposition techniques. These techniques break down the dependent variable, environmental impact, into multiple independent variables in order to analyze their effects and test for significance. For example, Lakshmanan and Han (1997) suggest that between 1970 and 1991, changes in travel propensity, population size, and GDP were the three principle forces driving transport energy consumption and emissions in the US. Wang et al. (2011) show that increased TCE in China between 1985 and 2009 can be explained by a modal shift and higher per capita economic activity. Achour and Belloumi (2016) analyze the transportation energy consumption in Tunisia and reveal that changes in GDP per capita are the primary driver of transportation energy consumption. Mazzarino's (2000) exploration of the transport sector in Italy between 1980 and 1995 reveals that growth in GDP is mainly responsible for increased transportation energy consumption.

A few studies compare TCE across multiple countries or look at different regions of one country. For example, Schipper et al. (1992) focus on passenger transportation in nine member countries of the Organization for Economic Cooperation and Development (OECD) between 1970 and 1987. They attribute changes in energy consumption and the resulting TCE to a shift toward more energy-intensive transportation modes and increases in travel activities, measured as passenger kilometers traveled per capita. Similarly, other studies in subsets of OECD countries (Scholl et al., 1996; Greening, 2004; Millard-Ball and Schipper, 2011) suggest that TCE can also be affected by (socio-)economic factors such as per capita GDP and fuel prices. Lu et al. (2007) compare TCE from highway transportation in Taiwan, Germany, Japan, and South Korea. For the 1990–2002 period, they find that economic growth and car ownership pushed TCE, whereas population intensity reduced TCE. Timilsina and Shrestha (2009a) conclude that economic growth and the sector's intensity of energy use drove the TCE of 20 Latin American and Caribbean countries between 1980 and 2005. For the same period, Timilsina and Shrestha (2009b) study 12 Asian countries, accounting for around 95% of total CE from developing countries in Asia, and illustrate that the transport sector's intensity of energy use, population growth, and per capita GDP were primary drivers of TCE. Marrero et al. (2021) focus on European transportation and analyze whether per capita CO_2 emissions from road transportation in 22 European countries converged over the 1990–2014 period. They find that economic activity and fuel prices affected the convergence process. Robaina and Neves (2021) study the CO_2 intensity in 27 EU countries between 2008 and 2018. They document that total per

[2] The ASIF-methodology focuses primarily on four determinants: activity (A), modal share (S), energy intensity (I), carbon intensity (F).

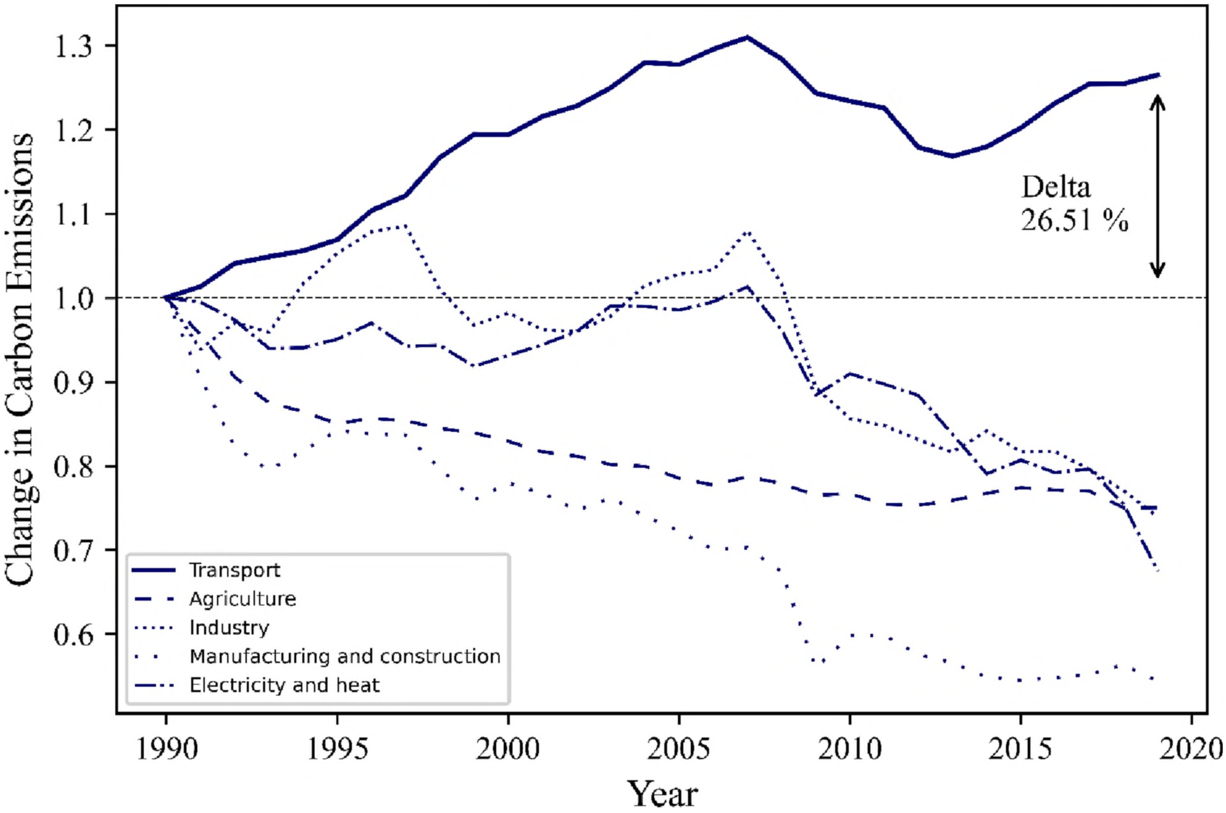

Fig. 2. Changes in carbon emissions by industry sector (EU 27 countries, 1990–2019). Note: Changes refer to 1990 levels in each industry sector. Data drawn from Ritchie et al. (2020).

capita energy consumption and per capita GDP are the principal drivers of CO_2 intensity.

York et al. (2003) point out two limitations of the *IPAT* identity and its extensions. First, the *IPAT* identity and its extensions are not suitable for hypothesis testing. Second, they assume a proportional relationship between factors, which may not always hold true. To overcome these limitations, Dietz and Rosa (1994, 1997) proposed a reformulation of the *IPAT* identity into a stochastic model called the *STIRPAT* model (the Stochastic Impact by Regression on Population, Affluence, and Technology model). Zhang and Nian (2013) use the *STIRPAT* model to conduct analysis in China between 1995 and 2010. They provide evidence that energy efficiency effectively reduces TCE, while economic development and population growth diminish their effect. Yang et al. (2015b) propose a transportation carbon emissions model for China based on spatial–temporal data for the 2000–2012 period. They analyze how socio-economics, urban forms, and transport sector developments affect emissions. Xu and Lin (2015, 2016) are two additional examples of analyses in China based on the *STIRPAT* model. Relatively little work has been carried out on European regions. Andrés and Padilla (2018) applied the *STIRPAT* model to examine the impact of population, economic activity, transport volume, and structural characteristics of transport activity on GHG emissions in the EU-28 between 1990 and 2014. In contrast to prior research, the authors observe that population and transport energy intensity are primary drivers of transport emissions.

Some studies analyze the effectiveness of specific emissions reduction measures, such as the appropriate design of environmental policies and the advancement of technologies. For example, Mendiluce and Schipper (2011) and González and Marrero (2012) discuss the effectiveness of a political diesel conversion campaign in Spain, i.e., to replace gasoline with diesel vehicles. Both studies affirm that the campaign has the potential to reduce TCE. However, Mendiluce and Schipper (2011) also find "rebound effects" of increased transportation activity resulting from the improved fuel efficiency of diesel vehicles. Building on the work by Jennings et al. (2013), Dennehy and Gallachóir (2018) analyze factors influencing energy demand and emissions from passenger cars in Ireland. They argue that, in addition to technological advances, effective policy measures are urgently needed to achieve significant TCE savings. In a recent study, Fuinhas et al. (2021) examine how the adoption of battery electric vehicles (BEVs) has impacted TCE across 29 EU countries. They find that BEVs are a promising technology with regard to decarbonizing the transport sector. Kazemzadeh et al. (2022), Koengkan et al. (2022) and Khurshid et al. (2023) are additional examples of studies that examine the role of technological advancements in combating TCE. In summary, all these studies underline the importance of technological innovation and policy redesign in addressing TCE.

All these studies, however, do not factor in spatial externalities in their analyses. While there is research in other industries such as the energy sector (Li and Li, 2020; Baig et al., 2022), relatively little consideration has been given to spatial autocorrelation patterns in the realm of transportation. The very limited body of the literature mainly focuses China. For example, Yu et al. (2013) use the spatial

Durbin model (SDM) to analyze the effects of transportation infrastructures on TCE over the period 1978–2009. They find positive spillover effects and show that the intensity of these effects varies across China's four macro-regions. Yang et al. (2019) investigate the spatial relationships for 30 Chinese provinces. Their analysis reveals that urban road density and per capita highway mileage are the critically influencing factors of TCE. If at all, studies of spatial externalities are available only for a small subset of European countries, e.g., Cantos et al. (2005), or for provinces of a single country, e.g., Moreno and López-Bazo (2007). No study has analyzed all European countries.

In summary, we have identified a research gap in the analysis of spatial autocorrelation patterns in carbon emissions from European land transportation. Similar studies conducted in China, such as those by Yu et al. (2013) and Yang et al. (2019), lead us to believe that spatial patterns may also exist in our data – further evidence is needed to confirm this. Li et al. (2019) demonstrate that taking into account regional heterogeneities in the transport sector, along with spatial dependence and spillover effects, can improve the quality of empirical analyses and, consequently, the resulting implications. With that in mind, our objective is to find evidence of spatial patterns in carbon emissions from European land transportation and account for them in the empirical analysis. By doing so, we aim to address the research gap in the field.

3. Data and methodology

3.1. Data

The analysis focuses on land transportation in Europe, thereby examining two transport modes (road and rail) and two transport types (freight and passenger). We use panel data of 26 European countries. These countries include the current 27 EU member states, excluding Malta and Cyprus, plus the United Kingdom due to its economic ties with the EU.

Our data covers a period of 25 years, namely from 1995 to 2019, selected based on data availability as we could not retrieve data for the period from 2020 onwards. Nevertheless, our studied period covers the major political and economic events that have significantly affected land transportation sector in Europa. For example, over this period, the EU underwent several enlargements leading to increased cross-border transport activities for numerous countries, and there has been a notable increase in the transport volumes of freight and passengers across Europe. Additionally, political measures, such as the Kyoto Protocol (United Nations, 1997), the Paris Climate Agreement (United Nations, 2015), and the European Green Deal (EU Commission, 2019), have marked important milestones in the global climate change mitigation and led to actions to reduce transportation emissions, including the emergence of new technologies and the introduction of fleet emission targets. Notably, our selected period excludes the external shock of the Covid-19 pandemic. While the Covid-19 pandemic had a profound impact on transportation, its short-term disruptions were temporary and largely reverted to pre-pandemic levels. Including this exceptional period in our analysis would have distorted the factors under consideration and led to flawed estimations.

Data on annual transport carbon emissions (TCE) for each country studied were collected from Ritchie et al. (2020). The TCE data are for the land transport sector only. Data on various transportation factors, including transportation activities and infrastructures, were obtained from the EU Commission (2022b), the OECD (2022) and the United Nations Economic Commission for Europe (UNECE, 2022). We also collected annual data on a country's population size (*POP*), land size (*CAR*), and the total energy structure (*ENS*), which illustrates the energy consumption mix and is measured as the shares of fossil fuels, including coal, oil, and gas, in total energy consumption. The last variable we collected is the energy intensity (*ENI*), which proxies technological development of the whole society and is measured as how many kilograms of oil equivalent are consumed to generate one thousand Euro of total GDP. As stated by Andrés and Padilla (2018), both energy structure and energy intensity are important variables for understanding energy use and its impact on the environment and economy. Energy structure can provide insights into the level of dependence on fossil fuels and the potential for transitioning to cleaner and more sustainable energy sources. Energy intensity can provide insights into the overall energy efficiency of an economy or sector and the potential for reducing energy consumption while maintaining economic growth. Table S2 in the Supplementary Material provides detailed information on the (raw) data collected, including information on the data sources and unit of measurements.[3]

From these (raw) data we derive the variables used in our analysis. First, we define variables measuring transportation intensity: TFT_t^i represents a country *i*'s annual total freight transportation volume expressed in million ton-kilometers; it is the sum of freight transported yearly by road and railway. Analogously, TPT_t^i represents a country *i*'s annual total passenger transportation volume expressed in million passenger-kilometers; it is the sum of passengers moved by road and railway yearly. Both variables correlate with the country's population size and limit country-wide compatibility. To increase compatibility, we calculate the transportation intensities by dividing the transport volumes by the population, i.e., we divide TFT_t^i and TPT_t^i by POP_t^i to construct the freight transportation intensity factor TFC_t^i and the passenger transportation intensity factor TPC_t^i, respectively. Second, we define variables that reflect the modal split of transport activities between road and rail: FRL_t^i represents a country *i*'s annual proportion of railway in the total freight transport, whereas PRL_t^i represents a country *i*'s annual proportion of railway in total passenger transportation. The variables are calculated as follows:

[3] A very small portion of the required data (4%) could not be retrieved. To redeem missing data, we deploy the linear interpolation techniques as detailed in the Supplementary Material.

$$FRL_t^i = RWF_t^i / TFT_t^i \tag{1}$$

$$PRL_t^i = RWP_t^i / TPT_t^i \tag{2}$$

where RWF_t^i and RWP_t^i are freight transport and passenger transport volume on railway.

Third, we define variables measuring the infrastructure density: MWL_t^i, ORL_t^i and RWL_t^i represent a country i's annual total length of motorway, road and railway infrastructure, respectively. The total length correlates with the country's area. We therefore use the infrastructure density in our empirical analyses and divide the network length by the total area, i.e., we divide MWL_t^i, ORL_t^i and RWL_t^i by CAR_t^i to construct the annual infrastructure density of motorways IMW_t^i, roads IOR_t^i and railways IRW_t^i, respectively. All variables express the network length per km^2. Descriptive statistics for the variables are presented in Table 1.

3.2. Empirical methods

3.2.1. Moran's I index

Moran's I, a statistical measure of spatial autocorrelation, was introduced by Moran (1950). Following previous studies, such as Li and Li (2020), we employ local and global Moran's I index tests to examine the spatial pattern of carbon emissions from European land transportation. Both tests can be deployed to test the spatial autocorrelation pattern, but on different scales. They assist in selecting the appropriate model for our empirical analysis of the influencing factors. Specifically, if spatial autocorrelation is present, a spatial panel data model is necessary for data analysis.

The global Moran's I index measures the overall clustering of spatial data. It is commonly defined as follows (Anselin, 1988):

$$I = \frac{\sum_i \sum_j w_{ij}(z_i - \bar{z})(z_j - \bar{z})}{S^2 \sum_i \sum_j w_{ij}}$$

$$\text{with } S^2 = \frac{\sum_i (z_i - \bar{z})^2}{n}, w_{ij} = \begin{cases} 1, ifprovincesiandjareadjacent \\ 0, otherwise \end{cases} \tag{3}$$

where S^2 is the sample variance, n is the number of observations, z_i and z_j are the observed values of regions i and j, $\bar{z}$ denotes the sample average, and w_{ij} is the i^{th}, j^{th} element of spatial weight matrix W, specifying the degree of dependence between regions i and j. When i and j are neighboring regions, $w_{ij} = 1$, and when regions i and j are not adjacent, $w_{ij} = 0$.[4] The index is calculated on an annual basis; however, for readability, the time index is omitted from the formula. The hypothesis test of Moran's I index is defined as follows:

$$Z = \frac{I - I_0}{\sqrt{Var(I)}} \tag{4}$$

with $I_0 = E(I)$.

Values of the global Moran's I index range from –1 to + 1. A positive significant global Moran's I index signals a spatial clustering phenomenon, indicating the adjacency of countries with similar TCE intensity, whereas a negative index implies spatial dispersion, implying the adjacency of countries with significantly different TCE levels.

Even in the absence of global autocorrelation or clustering, it is still possible to identify local clusters through the analysis of local spatial autocorrelation. Therefore, alongside the global Moran's I index, we also utilize the local Moran's I index test introduced by Anselin and Florax (1995) to examine the cluster effect of transport emissions in local areas. The local Moran's I test can be calculated as follows:

$$I_i = \frac{z_i - \bar{z}}{\frac{1}{n}\sum_i (z_i - \bar{z})^2} \sum_j w_{ij}(z_j - \bar{z}) \tag{5}$$

$$\text{with } w_{ij} = \begin{cases} 1, ifprovincesiandjareadjacent \\ 0, otherwise \end{cases}.$$

If $I_i > 0$, region i is adjacent to j^{th} regions with similar situations, indicating a high-to-high (H-H) or a low-to-low (L-L) cluster. In contrast, when $I_i < 0$, region i is adjacent to j^{th} regions with different situations, forming a high-low (H-L) or a low–high (L-H) spatial correlation mode. Using Moran's scatter, we plot all four spatial correlation modes in four quadrants. The first and third quadrants represent H-H and L-L clusters, and the second and fourth quadrants are L-H and H-L spatial correlation modes, respectively (Li and Li, 2020).

3.2.2. Spatial Durbin model and partial derivative method

If evidence of spatial autocorrelation is found, a spatial model must be used when analyzing influencing factors. Neglecting to do so would lead to biased estimates and potentially misleading findings (Yang et al., 2019). To account for spatial dependencies in the data, three spatial econometric models are commonly used in empirical analyses (LeSage and Pace, 2008; Elhorst 2012; 2014): the spatial

[4] In our spatial weight matrix, we consider the UK and France as adjacent to each other.

Table 1
Descriptive statistics.

	Unit	Min.	Median	Mean	Max.	Std. Dev.
POP	Thousand people	408.6	9,853.29	19,148.54	83,166.71	22,878.95
ENI	Kg of oil equivalent / thousand Euro	51.04	170.47	218.96	868.39	135.12
ENS	Percentage	29.92	81.47	79.72	99.98	14.94
TFC	Million tkm per thousand people	0.69	3.90	5.16	24.80	3.80
TPC	Million pkm per thousand people	3.35	10.92	10.41	16.12	3.01
FRL	Percentage	0.58	21.28	25.65	84.90	18.96
PRL	Percentage	0.57	7.27	8.17	32.22	4.73
IMW	M per km^2	0.00	10.93	29.76	187.48	43.79
IOR	M per km^2	32.53	1,213.61	1,905.65	13,026.97	2,496.12
IRW	M per km^2	3.27	45.86	101.16	497.48	110.61

Note: All entries are based on full panel data over the entire period studied. Std. Dev. stands for standard deviation.

autoregressive model (SAR), the spatial error model (SEM), and the spatial Durbin model (SDM). The SDM can be understood as a combination of the SAR and SEM. To enhance the clarity of the presentation, we will introduce the three spatial econometric models in a systematic manner. We commence with the definition of the SAR:

$$Y_{it} = \alpha + \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + \varphi X_{it} + \epsilon_{it} \tag{6}$$

with $w_{ij} = \begin{cases} 1, ifprovincesiandjareadjacent \\ 0, otherwise \end{cases}$,

where i and j denote regions i and j, respectively, and t represents year t. Y_{it} is an $N \times 1$ matrix of the dependent variable, and X_{it} is an $N \times K$ matrix of the independent variables. w_{ij} is the element of the constructed spatial weight matrix W. ρ is the estimated coefficient of the spatial lag dependent variable. φ is the estimated coefficient of the independent variables.α is a constant, and ϵ is a random error term with an independent and identical distribution.

We continue with the definition of the SEM. It takes the following form:

$$Y_{it} = \alpha + \varphi X_{it} + \varepsilon_{it} \tag{7}$$

with $w_{ij} = \begin{cases} 1, ifprovincesiandjareadjacent \\ 0, otherwise \end{cases}$ and $\varepsilon_{it} = \gamma \sum_{j=1}^{n} w_{ij} \varepsilon_{it} + \epsilon_{it}$,

where γ is the spatial autocorrelation coefficient of the random error term.

The SDM combines the SAR and SEM. It is written as follows:

$$Y_{it} = \alpha + \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + \varphi X_{it} + \theta \sum_{j=1}^{n} w_{ij} X_{ijt} + \epsilon_{it} \tag{8}$$

with $w_{ij} = \begin{cases} 1, ifprovincesiandjareadjacent \\ 0, otherwise \end{cases}$,

where φ and θ are the coefficients of the independent and spatial lag independent variables to be estimated. Furthermore, to control for spatial and time effects in the data, μ and λ are added to Eq. (8) to represent the spatial (individual) effect and the time effect, respectively. Thus, a spatial and time fixed effects SDM can be derived as follows:

$$Y_{it} = \alpha + \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + \varphi X_{it} + \theta \sum_{j=1}^{n} w_{ij} X_{ijt} + \mu_i + \lambda_t + \epsilon_{it} \tag{9}$$

with $w_{ij} = \begin{cases} 1, ifprovincesiandjareadjacent \\ 0, otherwise \end{cases}$.

The SDM provides a framework to analyze both direct and indirect (spillover) effects based on the estimates of the independent (φ) and spatial lag independent (θ) variables (Yang et al., 2015a). Specifically, the SDM offers insights into how a nation's transport emissions are influenced by internal factors (direct effects) as well as by its neighboring countries (indirect effects). However, as noted by LeSage and Pace (2010), using the SDM as only analytical framework to test for spillover effects can result in biased findings. To address this concern, we utilize the partial derivative method to validate both the direct and indirect effects, that have been calculated based on the SDM. Following LeSage and Pace (2009) and Elhorst, (2010), the SDM can be rewritten as follows:

$$Y_t = (I_n - \rho W)^{-1} \alpha + (I_n - \rho W)^{-1} X_t \varphi + (I_n - \rho W)^{-1} W X_t \theta + (I_n - \rho W)^{-1} \varepsilon \tag{10}$$

where I_n is an $N \times K$ identity matrix. The partial derivatives of dependent variable Y relative to the k^{th} explanatory variable X_k across n observations is thus expressed as follows:

$$\begin{bmatrix} \frac{\partial Y}{\partial X_{1k}} & \cdots & \frac{\partial Y}{\partial X_{Nk}} \end{bmatrix} = (I_n - \rho W)^{-1} [\varphi_k I_n + \theta_k W] \tag{11}$$

The direct impact is the average of the main diagonal elements of the $(I_n - \rho W)^{-1}[\varphi_k I_n + \theta_k W]$ matrix, and the indirect impact is the average of the off-diagonal elements of the matrix.

3.3. Transportation regression models

Within the analytical framework of the SDM, we incorporate transport regression models to examine the factors that influence carbon emissions from European land transportation. Following previous studies, such as Xu and Lin (2017) and Li and Li (2020), we construct our transport-specific regression models based on the *STIRPAT* model proposed by Dietz and Rosa (1997), which is a stochastic version of the *IPAT* identity first presented by Ehrlich and Holdren (1972). The classic *STIRPAT* model is formulated as follows:

$$I_t = \alpha + \beta_1 P_t + \beta_2 A_t + \beta_3 T_t + \varepsilon_t \tag{12}$$

where α and ε are the intercept and the random error term, respectively. I indicates impact, P is the population size, A is affluence, and T is the level of technological development (Xu and Lin, 2017). Since the *STIRPAT* model is conventionally adopted to analyze a region's total carbon emissions, we add variables to this model to make it specific to the transport sector. The selection of influencing factors was informed by the literature, e.g., Jennings et al. (2013) and Andrés and Padilla (2018), while also taking into account the available data that could be retrieved.

First, we construct our *transport activity model* to analyze the relationship between transport emissions and transport activities in detail. The variable selection in the model is partly inspired by the *IPAT* identity (Ehrlich and Holdren 1971; 1972) and the ASIF methodology (International Energy Agency 1997). Following Xu and Lin (2017), we use the variables POP_t^i and ENI_t^i as proxies for population and technological progress in country i for the year t. Affluence is normally represented by consumption, which is closely related to production (Wei, 2011). To proxy for production activities in the transport sector, we use two transportation intensity variables: TFT_t^i for freight transportation, and TPT_t^i for passenger transportation. As electrification in the transport sector is increasing, we also include ENS_t^i as a variable to proxy for the energy consumption structure, specifically the proportion of coal, oil, and gas used in electricity generation. In our transport activity model, to reflect the modal split in European land transportation, we also include two variables measuring the railways' share of freight (FRL_t^i) and passenger transportation (PRL_t^i). The transport activity model is defined as follows:

$$log(TCE_t^i) = \alpha + \beta_1 log(POP_t^i) + \beta_2 log(ENI_t^i) + \beta_3 log(ENS_t^i) + \beta_4 log(TFC_t^i) + \beta_5 log(TPC_t^i) + \beta_6 log(FRL_t^i) + \beta_7 log(PRL_t^i) + \varepsilon_t \tag{13}$$

where α and ε are the intercept and random error terms, respectively. Note that, to account for possible heteroscedasticity in the model, we applied natural logarithms to the variables.

Second, we construct our *transport infrastructure models* to analyze the effect of transportation infrastructure on carbon emissions from European land transportation. The variable selection is analogous to the transport activity model. Specifically, we incorporate the variables POP_t^i, ENI_t^i, and ENS_t^i as proxies for population, technological progress, and energy structure in country i for the year t. This approach allows us to account for the impact of these factors on the regression models, which is consistent with the broader framework of *STIRPAT* models. As explanatory variables, we incorporate the annual infrastructure density of motorways IMW_t^i, roads IOR_t^i and railways IRW_t^i, respectively. Our linear regression model (Model I1) is formulated as follows:

$$log(TCE_t^i) = \alpha + \beta_1 log(POP_t^i) + \beta_2 log(ENI_t^i) + \beta_3 log(ENS_t^i) + \beta_4 log(IMW_t^i) + \beta_5 log(IOR_t^i) + \beta_6 log(IRW_t^i) + \varepsilon_t \tag{14}$$

where α and ε are the intercept and random error terms, respectively.

According to the EKC hypothesis, carbon emissions follow an inverted U-shaped function of economic growth (Grossman and Krueger, 1991; Guo, 2021). As infrastructure development is closely linked to economic development, we construct a second infrastructure-related regression model to identify potential non-linear relationships between transportation infrastructure and transport emissions. This involves adding the squared variables of infrastructure density of motorways IMW_t^i, roads IOR_t^i and railways IRW_t^i, respectively. The non-linear transport infrastructure model (Model I2) is defined as follows:

$$log(TCE_t^i) = \alpha + \beta_1 log(POP_t^i) + \beta_2 log(ENI_t^i) + \beta_3 log(ENS_t^i) + \beta_4 log(IMW_t^i) + \beta_5 (log(IMW_t^i))^2 + \beta_6 log(IOR_t^i) + \beta_7 (log(IOR_t^i))^2$$
$$+ \beta_8 log(IRW_t^i) + \ + \beta_9 (log(IRW_t^i))^2 + \varepsilon_t$$

It is important to mention that we performed a stationarity test for each of the variables under investigation. This step was taken to mitigate the risk of obtaining spurious regression results and to enhance the overall credibility of our findings. Based on our data, we deploy the panel data stationarity test method proposed by Levin et al. (2002). Additionally, to test the robustness of our analysis, we employ the variance inflation factor (VIF) test, as suggested by O'brien (2007), and evaluate the extent of multicollinearity among the independent variables in our regression models.[5] The results are reported in Table S3 and S4 in the Supplementary Material.

4. Results

4.1. Spatial dependencies

We find evidence of positive spatial autocorrelation in carbon emissions from European land transportation, using global and local Moran's I indices. As shown in Table 2, the values of the global Moran's I index are consistently positive and significant for each year from 1995 to 2019. From this, it can be inferred a spatial agglomeration feature, indicating that countries with intensive TCE tend to be closely distributed geographically. Furthermore, the results provide evidence of a potential spatial spillover effect, whereby a country's TCE is influenced not only by domestic factors but also by the surrounding environment.

Alongside the global Moran's I index, we also calculated the local index to understand local clustering phenomena in the data. Fig. 3 shows the Moran's scatter illustrating the spatial autocorrelation of carbon emissions from European land transportation at a country-level for the years 1995 and 2019. The local Moran's I index test results for the countries in the Moran's scatter are reported in detail in Table S5 of the Supplementary Material. In 1995, 17 out of the 26 countries are positioned in the high-high (H-H) and low-low (L-L) quadrants of the Moran's scatter plot. In 2019, we observe 20 countries within the H-H and L-L quadrants of the Moran's scatter plot. Consequently, we observe an increased level of spatial autocorrelation, as indicated by the global Moran's I index values (0.3091 in 1995 and 0.3202 in 2019). Significantly, Germany, France, and the UK consistently occupy the first quadrant of the Moran's scatter plot in both 1995 and 2019. This indicates a region characterized by high TCE intensity and forming a persistent H-H cluster.

Given the significant results from the global and local Moran's I index tests, indicating a stark spatial dependence pattern in TCE, it is crucial to consider this when examining the influencing factors. Therefore, we choose to employ a spatial econometric model in our empirical analyses.

4.2. Transport activity model

In this section, we explore relationships between transport activities and TCE. To understand whether it is necessary to control for spatial individual and time effects in the panel data and which spatial econometric model best suits our data, we follow the test procedure used in previous studies to first estimate non-spatial models. Table 3 presents the estimation results using a pooled ordinary least squares model (OLS), a panel data random-effects model (REM), a spatial (individual) fixed-effects model (SFM), a time fixed-effects model (TFM), and a spatial and time fixed-effects model (STM).

Following Li and Li (2020), we also report the results from log-likelihood, likelihood ratio (LR), Durbin-Wu-Hausman (Hausman test), and Lagrange multiplier (LM) tests for spatial lags and errors and robust spatial lags and errors to aid our model selection (Durbin, 1954; Wu, 1973; Hausman, 1978). The results of the LR test imply that the REM, SFM, TFM, and STM fit the data better than the OLS. In addition, we deploy the Hausman test to determine whether a random- or fixed-effects model is more suitable for investigating our data. The results reported in Table 3 indicate the superiority of the fixed-effects models. Based on the results of the log-likelihood, LR, and Hausman tests, the model deployed in our analysis must control for both individual and time effects, leading us to the STM. Based on the STM, we examine whether the model should include spatial lag variables (LM spatial lags) and spatially autocorrelated error terms (LM spatial errors). As shown in Table 5, the test statistics for LM spatial error and lag and robust spatial error and lag are all highly significant at the 1% level. Based on all these test results, we follow the recommendations of LeSage and Pace (2009) in deploying a spatial and time fixed-effects SDM for our transportation activities and modal splits analysis (Li and Li, 2020).

In Table 4, we list the estimation results of the SDM, and direct and indirect effects from the transport activity model. As the coefficients indicating direct and indirect effects in the SDM may be imprecise, we only interpret the sign and significance of the estimated coefficients in the SDM and judge the effect size according to the estimated effects. As shown, the factor loading on population size variable is not significant, whereas the coefficient of spatial lag population is significant and negative. In contrast, the factor loading on energy structure is positive and statistically significant, indicating that local TCE is positively correlated with fossil fuel consumption for electricity generation. Unsurprisingly, energy intensity is negatively correlated with both domestic and international TCE. As previously illustrated in Fig. 2, with developments in the EU, TCE increased significantly over the period studied. Regarding the intensity of transportation activities, we observe that freight transportation does not influence local TCE, but has a significant spillover effect on TCE in neighboring countries. In contrast, passenger transportation intensity is positively correlated with local TCE. However, the factor loading on spatial lag passenger transportation intensity is insignificant. With respect to the modal split, we find that the coefficient of the proportion of railway use in freight transportation is negative for domestic TCE and positive for TCE in neighboring countries. In comparison, the proportion of railway use for passenger transportation is not significantly correlated with changes in TCE.

Table 4 also presents the estimated direct and indirect effects of each variable. In general, the estimated direct and spillover effects are in line with the estimation results of SDM, except that the impact magnitude varies slightly. Our double-log model enables us to

[5] By constructing two separate models (transport activity model and transport infrastructure model), we can avoid statistical conflicts related to multi-collinearity.

Table 2
Global Moran's *I* index.

Year	*I*	*p*-value	Year	*I*	*p*-value
1995	0.3091**	0.02	2008	0.3521**	0.01
1996	0.3148**	0.02	2009	0.3381**	0.01
1997	0.3143**	0.02	2010	0.3424**	0.01
1998	0.3274**	0.02	2011	0.3571***	0.01
1999	0.3446**	0.01	2012	0.3530**	0.01
2000	0.3702***	0.01	2013	0.3556***	0.01
2001	0.3618***	0.01	2014	0.3476**	0.01
2002	0.3640***	0.01	2015	0.3336**	0.01
2003	0.3654***	0.01	2016	0.3277**	0.02
2004	0.3724***	0.01	2017	0.3208**	0.02
2005	0.3750***	0.01	2018	0.3220**	0.02
2006	0.3603***	0.01	2019	0.3202**	0.02
2007	0.3454**	0.01			

Note: ***, **, and * denote significance at the 0.1%, 1%, and 5% levels, respectively.

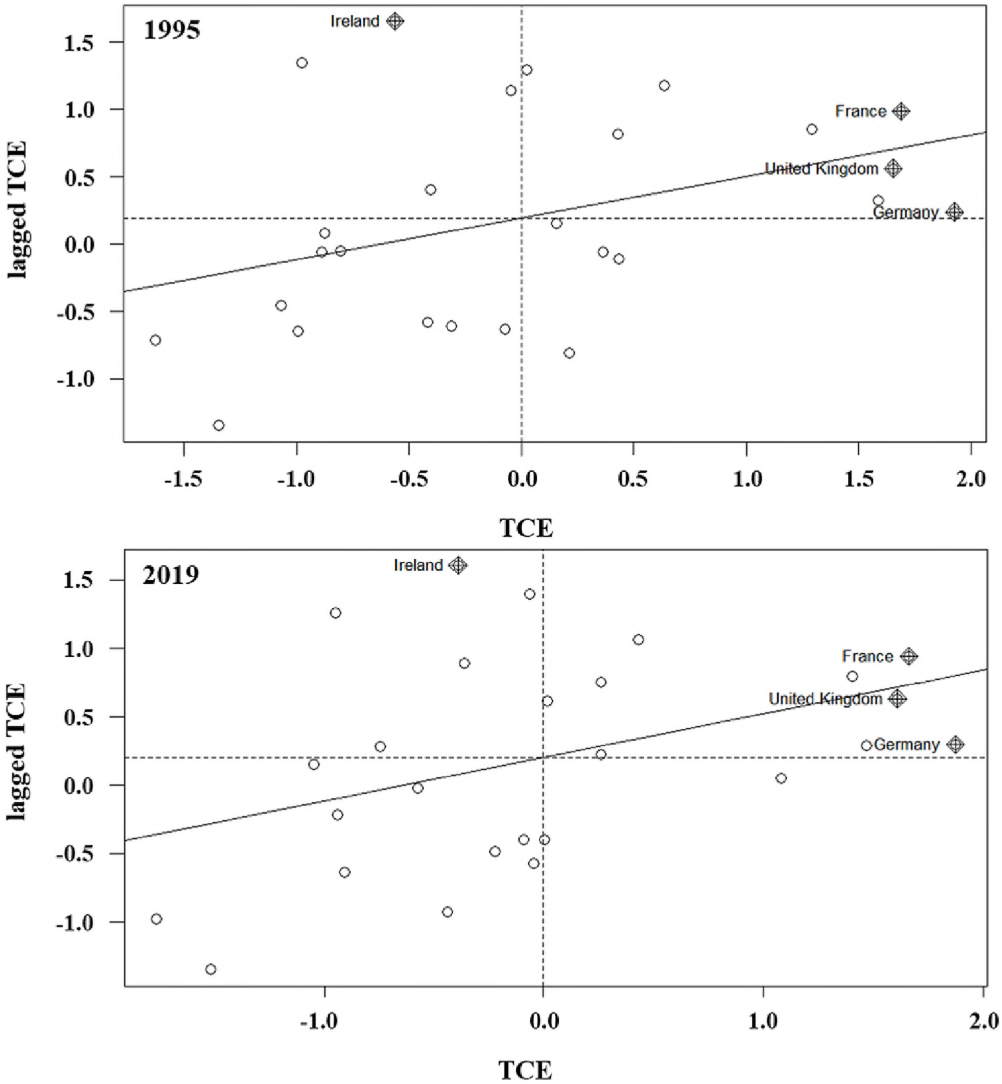

Fig. 3. Moran's scatter of transport emissions in 1995 and 2019.

Table 3
Non-spatial model estimation results (Transport activity model).

	OLS	REM	SFM	TFM	STM
Intercept	6.82***	6.79***			
	(0.3255)	(0.5099)			
log(*POP*)	0.8472***	0.8712***	0.4678***	0.8515***	0.0120
	(0.0083)	(0.0327)	(0.1207)	(0.0079)	(0.1301)
log(*ENS*)	0.2686***	0.4313***	0.3384***	0.1900***	0.1912*
	(0.0430)	(0.0688)	(0.0749)	(0.0414)	(0.0779)
log(*ENI*)	−0.2795***	−0.1842***	−0.1853***	−0.3540***	−0.2055***
	(0.0282)	(0.0325)	(0.0329)	(0.0277)	(0.0466)
log(*TFC*)	0.1944***	0.1751***	0.1603***	0.2298***	0.0904***
	(0.0163)	(0.0209)	(0.0226)	(0.0161)	(0.0236)
log(*TPC*)	0.9255***	0.4385***	0.3060***	0.8653***	0.1330*
	(0.0426)	(0.0579)	(0.0595)	(0.0407)	(0.0620)
log(*FRL*)	−0.1071***	−0.0612***	−0.0917***	−0.1109***	−0.1256***
	(0.0120)	(0.0163)	(0.0187)	(0.0114)	(0.0185)
log(*PRL*)	0.1440***	−0.0585*	−0.0723*	0.1250***	−0.0683*
	(0.0167)	(0.0276)	(0.0307)	(0.0159)	(0.0300)
Log-likelihood	86.96	528.41	567.04	137.09	622.74
LR test		882.91***	960.17***	100.27***	1,071.60***
Hausman test			116.26***	16.65*	591.73***
LM spatial lag					97.61***
Robust LM spatial lag					67.21***
LM spatial error					40.69***
Robust LM spatial error					10.28***

Note: The results of the LR test are benchmarked against the pooled OLS model, and the results of the Hausman test are benchmarked against the REM. The results of LM tests for spatial lag and error and robust spatial lag and error are also presented. Standard errors for the coefficients are reported in parentheses. ***, **, and * denote significance at the 0.1%, 1%, and 5% levels, respectively.

Table 4
Estimates for the spatial Durbin model and partial derivative method (Transport activity model).

	Spatial Durbin model		Partial derivative method	
	Independent	Spatial lag	Direct effects	Indirect effects
log(*TCE*)		0.0435		
		(0.0306)		
log(*POP*)	0.1401	−0.3283***	0.1350	−0.3509***
	(0.1292)	(0.0717)	(0.1306)	(0.0775)
log(*ENS*)	0.2909***	−0.0350	0.3028***	−0.0420
	(0.0683)	(0.0444)	(0.0711)	(0.0444)
log(*ENI*)	−0.0900*	−0.1423***	−0.0921*	−0.1495***
	(0.0422)	(0.0172)	(0.0404)	(0.0172)
log(*TFC*)	0.0054	0.0476***	0.0030	0.0501***
	(0.0213)	(0.0134)	(0.0228)	(0.0137)
log(*TPC*)	0.1942***	−0.0599	0.1997***	−0.0632
	(0.0545)	(0.0380)	(0.0602)	(0.0416)
log(*FRL*)	−0.1351***	0.0299*	−0.1426***	0.0302*
	(0.0167)	(0.0121)	(0.0183)	(0.0128)
log(*PRL*)	−0.0328	0.0321	−0.0334	0.0342
	(0.0270)	(0.0178)	(0.0290)	(0.0178)

Note: Spatial lag variables indicate the $W \bullet Y$ and $W \bullet X$ components in Eq. (8). Standard errors for the coefficients are reported in parentheses. ***, **, and * denote significance at the 0.1%, 1%, and 5% levels, respectively.

interpret the estimated effect size. For instance, a 1% change in passenger transportation intensity is positively correlated, on average, with a 0.1997% increase in domestic TCE. In contrast, a 1% increase in the proportion of railway freight transportation is correlated, on average, with a −0.1426% change in domestic TCE.

4.3. Transport infrastructure models

In this section, we explore relationships between developments in transportation infrastructures and TCE. We focus on three types of transportation infrastructure, namely highways, roads, and railways. Unlike previous analyses, we study both linear and non-linear relationships. The non-spatial model estimation results for the linear and non-linear infrastructure models, i.e., Models I1 and I2, can be found in Table S6 of the Supplementary Material. Similar to the transport activity analysis, the results also suggest the superiority of the fixed spatial- and time-effects SDM. In Table 5 and Table 6, we report the estimation results from the SDM, and direct and indirect effects from both the linear and non-linear models, respectively.

Table 5
Estimates for the spatial Durbin model and partial derivative method (linear Transport infrastructure model – I1).

	Spatial Durbin model		Partial derivative method	
	Independent	Spatial lag	Direct effects	Indirect effects
log*(TCE)*		−0.0304		
		(0.0370)		
log*(POP)*	0.3605***	−0.5237***	0.3419***	−0.5124***
	(0.0970)	(0.0612)	(0.0894)	(0.0659)
log*(ENS)*	0.4465***	0.1322*	0.4285***	0.1304***
	(0.0731)	(0.0530)	(0.0778)	(0.0447)
log*(ENI)*	−0.2557***	−0.1490***	−0.2474***	−0.1456***
	(0.0419)	(0.0173)	(0.0416)	(0.0168)
log*(IMW)*	0.0834***	0.0373**	0.0797***	0.0369***
	(0.0146)	(0.0116)	(0.0150)	(0.0123)
log*(IOR)*	−0.0871***	0.0335**	−0.0838***	0.0319***
	(0.0140)	(0.0104)	(0.0142)	(0.0108)
log*(IRW)*	0.2930***	0.0272	0.2870***	0.0312
	(0.0798)	(0.0489)	(0.0809)	(0.0451)

Note: Direct and indirect effect estimations are shown. Spatial lag variables indicate the W•Y and W•X components in Eq. (8). Standard errors for the coefficients are reported in parentheses. ***, **, and * denote significance at the 0.1%, 1%, and 5% levels, respectively.

Table 6
Estimates for the spatial Durbin model and partial derivative method (non-linear Transport infrastructure model – I2).

	Spatial Durbin model		Partial derivative method	
	Independent	Spatial lag	Direct effects	Indirect effects
log*(TCE)*		−0.0300		
		(0.0350)		
log*(POP)*	0.2921**	−0.6908***	0.2865***	−0.6710***
	(0.0920)	(0.0627)	(0.0923)	(0.0591)
log*(ENS)*	0.4033***	0.1757***	0.3873***	0.1735***
	(0.0694)	(0.0513)	(0.0716)	(0.0476)
log*(ENI)*	−0.1627***	−0.1558***	−0.1523***	−0.1530***
	(0.0463)	(0.0187)	(0.0475)	(0.0188)
log*(IMW)*	0.2213***	−0.1208***	0.2163***	−0.1172***
	(0.0297)	(0.0235)	(0.0318)	(0.0240)
$(\log(IMW))^2$	−0.0436***	0.0459***	−0.0428***	0.0444***
	(0.0077)	(0.0053)	(0.0077)	(0.0055)
log*(IOR)*	−0.3517***	−0.0714	−0.3474***	−0.0671
	(0.0902)	(0.0587)	(0.0848)	(0.0601)
$(\log(IOR))^2$	0.0222***	0.0072	0.0220***	0.0069
	(0.0066)	(0.0043)	(0.0062)	(0.0044)
log*(IRW)*	0.4797	0.5854**	0.4509	0.5703***
	(0.2500)	(0.1814)	(0.2515)	(0.1777)
$(\log(IRW))^2$	−0.0236	−0.0594**	−0.0203	−0.0578***
	(0.0327)	(0.0201)	(0.0320)	(0.0202)

Note: Direct and indirect effect estimations are shown. Spatial lag variables indicate the W•Y and W•X components in Eq. (8). Standard errors for the coefficients are reported in parentheses. ***, **, and * denote significance at the 0.1%, 1%, and 5% levels, respectively.

The results show that the estimated coefficients for population, energy structure, and energy intensity and the spatial lag results are all significant. These factor loadings are in line with those in the transportation activities model. For the first transportation infrastructure variable, namely motorway density, the estimated direct and indirect effects are positive and significant at the 1% level in the linear model. In the non-linear model, all the estimated coefficients of both motorway density and motorway density square for both direct and indirect effects estimations are highly significant. Using the estimated effect sizes, this implies that the relationship between motorway (*IMW*) density and local TCE takes the form of $TCE = -0.0428IMW^2 + 0.2163IMW$, implying that this relationship has an inverted U shape. Thus, the slope of the relationship between motorway density and TCE depends on the level of motorway density itself. By differentiating this equation: $\partial_{TCE}/\partial_{IMW} = -0.0856IMW + 0.2163$, and setting $\partial_{TCE}/\partial_{IMW} = 0$, namely $-0.0856IMW + 0.2163 = 0$, we calculate where TCE are maximized, namely at $IMW = 2.5269$. At low levels of motorway density, the slope is positive, such that TCE increase with motorway infrastructure development. After reaching the maximum, TCE decrease with motorway density. In contrast, the indirect effect of motorway density and TCE in neighboring countries takes the form of $TCE = 0.0444IMW^2 - 0.1172IMW$, suggesting a U shape.

As shown in Fig. 4a, the direct and indirect effects between motorway infrastructure and TCE can have opposite shapes. When estimating the direct effect, we observed that both the sample mean and median were located on the left-hand side of the parabola where the slope is positive, indicating a positive factor loading on motorway density in the linear model.

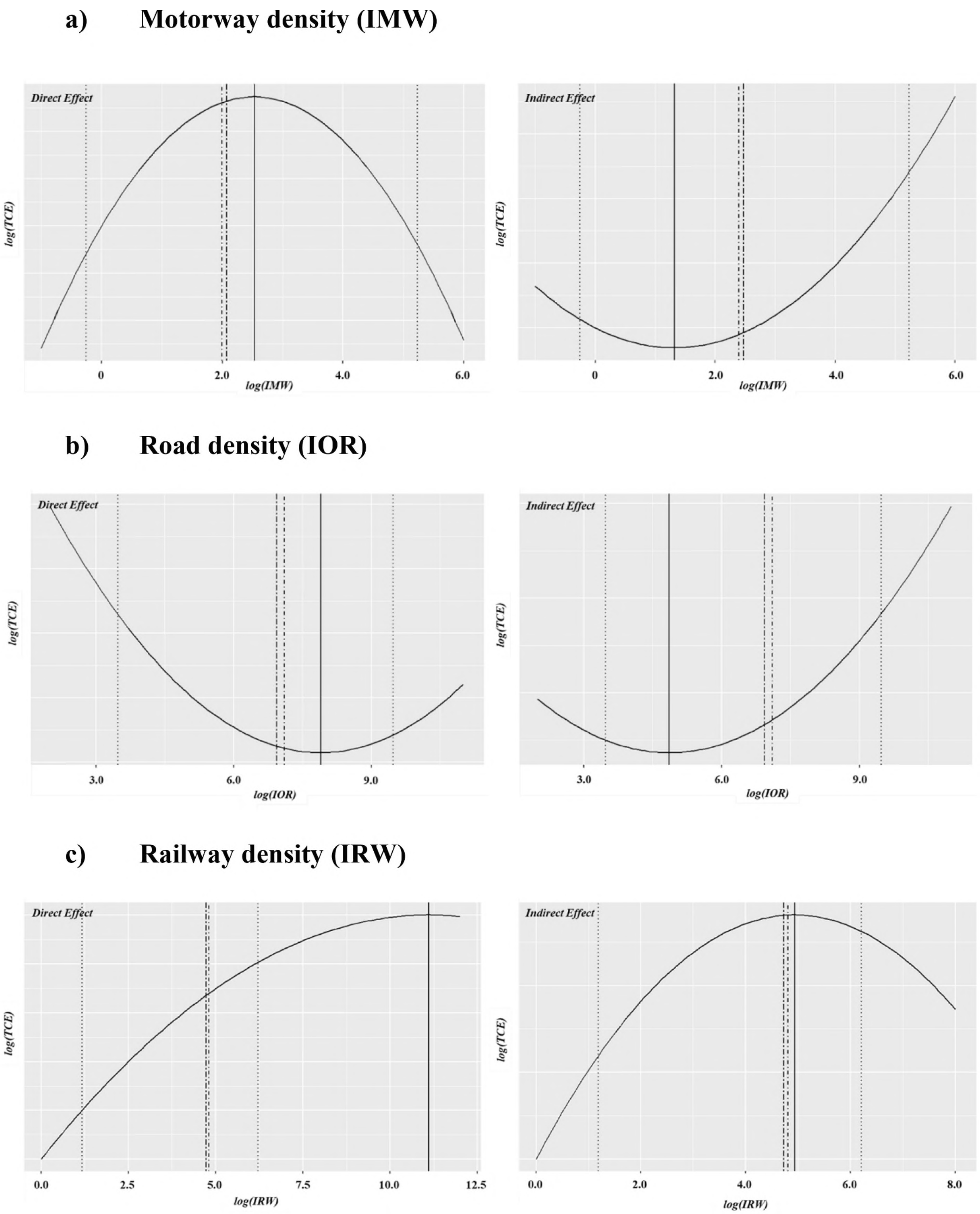

Fig. 4. Non-linear relationships between infrastructure and transport emissions (direct and indirect effects). Note: The dotted line indicates the sample range, the dashed line indicates the sample mean, the dot-dashed line indicates the sample median, and the solid line indicates where the minimum or maximum occurs.

Regarding road density (*IOR*), in the linear model, increasing road density is negatively correlated with local TCE, but positively correlated with TCE in neighboring countries. In Model I2, we observe a significant non-linear relationship for direct TCE, as the estimates for both road density and quadratic road density squared are significant. Using the estimated direct effect size, the direct effect of road density on TCE takes the form of $TCE = 0.0220IOR^2 - 0.3474IOR$. In differentiating this equation, we calculate that TCE are minimized at $IOR = 7.8955$, corresponding with a density of 2,685.17 m/km^2. In terms of the indirect effect, we observe that the estimates for both road density and road density square are non-significant. However, these observations do not allow us to conclude that the relationship between road density and TCE in adjacent countries is solely linear. They only indicate that our data range lies largely on one side of the non-linear relationship. In other words, our observations are heavily concentrated on one side of the parabola, leading to a curvilinear function that does not reach a peak or nadir, nor turn around. Thus, we only observe that the coefficients of road density are significant in the linear model for indirect effects. As illustrated in Fig. 4b, the indirect effect of road density on TCE is also U-shaped. Both the mean and median are on the right-hand side of the parabola where the slope is positive. More specifically, only 4.77% of observations are located on the left-hand side of the axis of symmetry. Therefore, the non-linear relationship is not significant.

Regarding railway density (*IRW*), in the linear model, the estimated coefficient of railway density is positive and significant for the direct effect, whereas the spillover effect of railway density on TCE is non-significant. However, in the non-linear model, the opposite situation is identified. In the direct-effects estimations, the estimates for both railway density and quadratic railway density squared are not significant, while in the indirect-effects estimations, both coefficients are significant, forming an inverted U-shaped relationship. As previously mentioned, non-significant factor loadings on railway density and squared railway density do not rule out a potential non-linear relationship. In Fig. 4c, we plot both the direct and indirect effects of railway density on TCE. In the direct effects estimation, our data range lies only on the left-hand side of the parabola, far away from the axis of symmetry. Therefore, in the linear model, the coefficient of railway density is positive and significant. In contrast, in the indirect effects category, both the sample mean and median are close to the vertex, where the slope is zero. Thus, in the linear model, the factor loading on railway density is found not to be significant. However, since the observations are distributed on both sides of the parabola, the non-linear relationship is significant.

5. Discussion and policy implications

While other sectors in the EU showed declines in carbon emissions, those in the transport sector increased significantly, as illustrated in Fig. 2. Furthermore, different from previous studies, such as Zhang and Nian (2013), our model estimates indicate that technological development is negatively correlated with TCE. All these observations underline the uniqueness of the transport sector in Europe, and the difficulty of mitigating TCE. Thus, this study not only addresses existing research gaps, but also has practical significance and can stimulate evidence-based policy discussions between industry, government, and researchers, towards accelerated decarbonization in European land transportation.

First, using the global Moran's *I* test results, we are the first to find evidence of spatial autocorrelation patterns in TCE across the European countries studied. The results underscore the international nature of land transportation, which involve cross-border movements of goods and people. Since the identified spatial pattern is closely related to the spillover effect, we conclude that management of transport emissions in one country is also a concern for others. In addition, the local Moran's *I* index provides evidence of a clustering or agglomeration effect in TCE, whereby countries with similar TCE intensities tend to be closely distributed. As illustrated in Fig. 3 and detailed in Table S3 of the Supplementary Material, Western European countries such as Germany, France, and the UK are in the H-H cluster, whereas Eastern European countries tend to be found in the L-L cluster. These findings imply a strong correlation between economic development and the transport sector. In this sense, our study is in line with the prevailing opinion from other researchers, e.g., Lakshmanan and Han (1997), Grossman and Krueger (1991), and Guo (2021), suggesting economic development drives transport activities, and vice versa. Countries with robust economic activities experience a corresponding increase in demand for transportation services and their carbon emissions, and they are therefore particularly called upon to take more decisive steps towards sustainable transport (Robaina and Neves, 2021).

Our results indicate that the intensity of the TCE spatial pattern is not stable but varies over time. The evolution of the global Moran's *I* index, plotted in Fig. 5, shows that macroeconomic events, such as the Asian financial crisis in 1997, the bursting of the dot-com bubble in 2000, the global financial crisis in 2008, and the European debt crisis, may impact on this intensity. This again emphasizes the close relationship between the EU's economy and transport sector. Rather surprisingly, comparison of the global Moran's *I* index between 1995 and 2019 shows that the EU-wide spatial dependence pattern has become more pronounced, with the 1995 level being the lowest in the period under review. It is worth noting that in 1995, most countries in Eastern Europe were not in the EU. As a supranational political and economic union, the EU removes trade barriers, creates favorable business environments, and thus provide incentives for cross-border economic activities among its member states. Under this framework, we would expect reduced clustering and greater assimilation among the EU member states over time. This would correspond with a declining trend in the yearly global Moran's *I* index. Instead, we observe the opposite, namely a strengthened clustering effect in the EU, indicating some heterogeneity in national transport sectors, and suggesting that full assimilation among EU member states is likely to occur with considerable delay, if at all.

The observed heterogeneity and interdependence in TCE underpin the importance of close cooperation between European countries in decarbonizing the land transport sector. This requires joint EU-wide forces to reduce TCE more effectively. In this process, the EU and its established institutions play a central role in guiding, monitoring, and controlling reduction efforts in the land transport sector, for example, through the European Parliament's Committee on Transport and Tourism, and the European Environment Agency. As these mechanisms are already in operation, these committees might construct an overarching strategic roadmap towards greater sustainability in the EU land transport sector such as European Green Deal (EU Commission, 2019). However, for effective implementation, it is crucial for EU member states from different spatial clusters as illustrated in Fig. 3 to engage in smaller sub-committees. This is consistent with the findings by Dolge et al. (2023), suggesting that national policies are important for effective decarbonization of EU land transportation, and sustainability measures should be adapted to the specificities of the different regions in the EU.

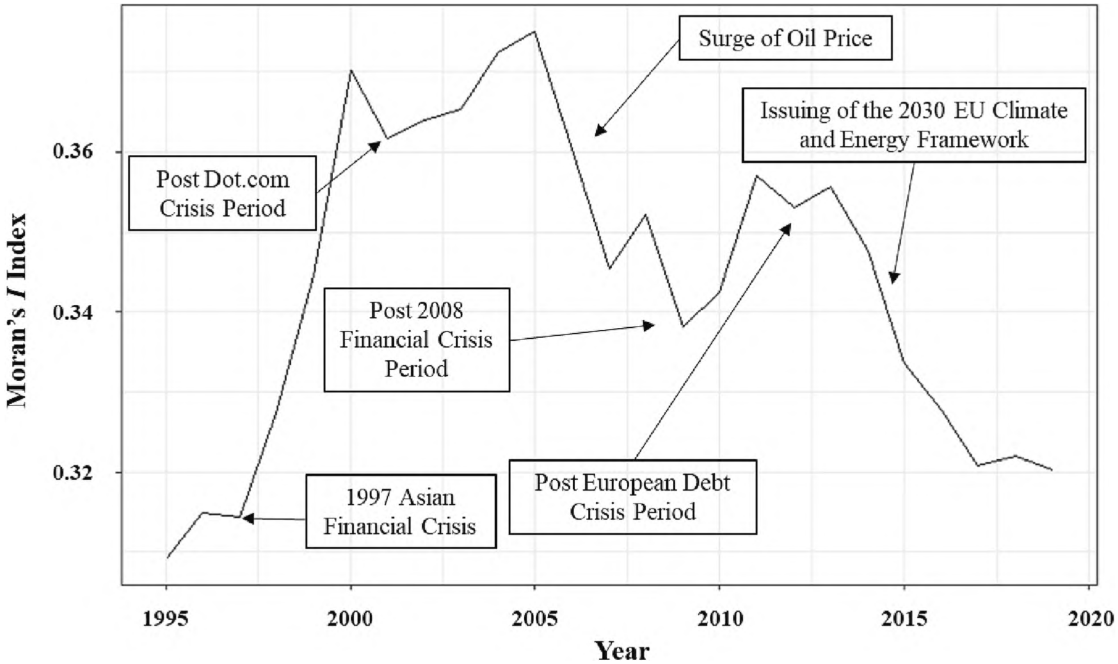

Fig. 5. Evolution of the global Moran's *I* index.

Second, the empirical results based on the transport activity model and both linear and non-linear transport infrastructure models provide can be vital in guiding future policymaking towards a more environmentally friendly and sustainable transport sector in Europe. They provide valuable insights into a nation's direct effects and the effects from neighboring countries (indirect effect) on its transport emissions.

The estimation results from our transport activity model indicate a positive correlation between transport intensity and transport-related emissions in the EU. In other words, as the intensity of freight and passenger transport increases, so do the sector's emissions. Specifically, our study is the first to reveal that passenger transport intensity has a significant positive correlation with the sector's domestic emissions, whereas freight transport intensity has a significant positive effect on emissions in neighboring countries. Regarding modes of transport, our empirical analysis suggests that TCE decrease, or at the very least remain stable, when greater proportions of freight and passengers are transported by rail rather than road. This is evidenced by a significant negative correlation between railway freight and domestic emissions from the transport sector.

In summary, considering the spatial spillover effects, our analysis emphasizes the importance of collective efforts from governments and other transport stakeholders to mitigate the environmental consequences of transport activities in Europe. Previous research has already demonstrated that technological advancements, such as the proliferation of zero-emissions vehicles, can reduce TCE (Fuinhas et al., 2021; Kazemzadeh et al., 2022; Koengkan et al., 2022). However, this reduction effect can only be implicitly inferred from the results obtained in the investigation, as technological development is negatively correlated with TCE. Our results explicitly state that a reduction in TCE can be achieved by reducing transportation intensity and encouraging the shift from road to rail.

In line with our empirical results, one promising measure seems to be the EU's expansion of the European Emissions Trading System (ETS) to include the transport sector (EU Commission, 2021). Especially in light of the uncovered spatial dependencies in carbon emissions, it is noteworthy that the ETS is effective in all EU member countries. The ETS is understood as a pricing mechanism to control mobility and transport behavior (Urrutia et al., 2021). By increasing the price of carbon emissions, the cost of using fossil fuel-based transportation options becomes less economically attractive. This mechanism holds promise, particularly considering that most vehicles on the road still rely on fossil fuels (EU Parliament, 2019).

On a conceptual basis, the ETS is expected to have two effects in reducing carbon emissions as the price for carbon emissions increases. First, it discourages unnecessary mobility and transportation, leading to a decrease in transport intensities. Second, it promotes the adoption of eco-friendly, less carbon-intense modes of transportation, such as rail, thereby increasing its share in the overall transportation system. Both effects are in line with our empirical results. However, the quantification of these effects is beyond the scope of this research. We therefore recommend conducting further research to quantify the effectiveness of the ETS in reducing carbon emission from transportation, building upon existing simulations such as the one conducted by Heinrichs et al. (2014). This would require examining various aspects, such as the social compatibility of the ETS, which has been raised as a concern by Stenning et al. (2020).

We conclude that while the extension of the ETS to the transport sector can be a positive first step, additional policies should be explored to ensure a socially fair and effective transition towards sustainable mobility. For example, implementing structural improvements in the rail transport system may be necessary to encourage people to choose trains over cars or buses (Bešinović, 2020).

The decision to choose a particular mode of transportation is not solely determined by cost, but also by non-monetary factors, including the availability and reliability of rail services, the distance and frequency of travel, and the convenience of connecting modes of transport.

In this respect, our transport infrastructure models can provide valuable insights. Our linear model reveals a significant positive correlation between rail network density and domestic TCE, while our non-linear model is the first to uncover a significant inverted U-shaped relationship between rail network density and TCE in neighboring countries. Past the inflection point of the parabola, further rail network expansion is associated with reduced TCE in neighboring countries, as illustrated in Fig. 4c. The two models in combination show that changing rail transport systems is a complex undertaking that must be shared across the EU.

The results of the linear model initially contradict the notion that rail is environmentally friendly. However, this can be explained through additional in-depth analyses. First, the non-linear estimations should not be ignored, even if the estimated factor loadings are not significant. As illustrated in Fig. 4c, the non-linear relationship between railway network density and domestic TCE takes the shape of an inverted U. Our data are distributed only on the left-hand side of the parabola and the turning point is not covered, suggesting the significance of the estimated linear impact of railway density on domestic TCE. Second, in an unreported test, we find evidence that the density of a country's rail network is positively correlated with railway transport intensity, with a correlation coefficient of 0.3260, but is relatively weakly correlated with the rail proportion of total freight transport volumes, with a correlation coefficient of 0.0102. This suggests that inefficiencies in European rail transport will overcompensate for emissions savings from a modal shift. Therefore, it is assumed that a denser rail network will lead to increased transport intensity and higher TCE. This finding is also consistent with the results of our transport activity model.

These findings lead us to conclude that strategic investments in European rail infrastructure have the potential to significantly reduce TCE. However, this is not about merely building a longer rail network, but about improving it holistically, by constructing sustainable rail tracks as well as increasing rail's share of total transport volumes. Interestingly, in contrast to road infrastructure, the total length of European rail infrastructure actually decreased by 6% between 1995 and 2019 (EU Commission, 2022a). In light of the complex spatial dependencies in rail transport, EU-wide initiatives like the Trans-European Transport Network are again called on to complement national initiatives, such as Deutsche Bahn's Strong Rail campaign in Germany. Our transport activity model highlights the critical significance of focusing on rail freight transport. Increasing rail's share of total freight transport will reduce emissions from the transport sector. The New Silk Road initiative might serve as a model to address system bottlenecks and technical barriers in order to promote smooth and seamless cross-border logistics operations. Electrification and harmonization of European rail infrastructure are crucial areas that require focused attention.

The EU Commission (2022) reports that electrification rates vary widely across European countries, between under 10% to almost 90% in 2019. Electrification means equipping the lines with infrastructure to operate electric locomotives. We should keep in mind that reducing the proportion of coal, oil, and gas in total energy consumption has been found to be an essential factor in decarbonizing the transport sector. As Tables 4, 5 and 6 show, energy structure is estimated to have a positive direct and indirect effect on transport emissions. For the sake of completeness, we must mention that decarbonization of the energy supply sector also plays an important role but is not discussed in this paper.[6] Once the entire rail infrastructure has been electrified, the diesel-fueled locomotives that predominate in freight transport can be successively replaced and withdrawn from service. To promote the adoption of electric locomotives, the EU might also consider fiscal incentives similar to those for road vehicles. In summary, this will help deliver a comprehensive rail system modernization program.

Finally, our study provides valuable insights into the relationship between road transport infrastructures, i.e., motorway and other road infrastructure, and transport emissions. First, motorway density is identified as having positive effects on both domestic and international transport emissions in the linear model. In the non-linear model, the direct effect takes the form of an inverted-U, whereas the spillover effect is U-shaped. Second, density of non-motorway road infrastructure is found to have a negative direct effect on domestic transport emissions in the linear model. However, in the non-linear model, the direct effect exhibits a U-shaped relationship. Additionally, we find a positive linear relationship between a country's road density increases and transport emissions in neighboring countries, i.e., when a country expands its road network, transport emissions in neighboring countries increase.

Based on these observations, it may seem logical to assume that increasing the number of roads would improve traffic conditions and reduce transport emissions. Essentially, if the road network is insufficient or lacks coverage, the high concentration of vehicles on existing roads can lead to frequent braking and congestion. Consequently, increasing road density initially has a positive effect on reducing transport emissions. However, there comes a threshold where further increases in road density actually contribute to higher transport emissions. Moreover, when considering the positive indirect effects of infrastructure planning on transport emissions, the development of road infrastructure can be viewed as a catalyst for increased road mobility, particularly in neighboring countries.

Our findings emphasize the importance of a collaborative, pan-European approach to road transport infrastructure development, considering its significant spillover effects. Similar to railway infrastructure, the focus should not solely be on expanding the network size. Instead, our analysis suggests the existence of a "sustainability sweet spot" for infrastructure development within the EU. Additionally, unreported analysis reveals a negative correlation coefficient of −0.2337 between a country's highway network density and the proportion of freight transported by rail. This suggests a cannibalization effect of highway infrastructure expansion on railway transport. As motorway density increases, the proportion of freight transported by rail decreases, contradicting the overall objective of shifting from road to rail. Therefore, we conclude that transport infrastructure development should be approached holistically, with

[6] For more details, see Nichols et al. (2015) and Papadis and Tsatsaronis (2020).

simultaneous consideration of road and rail transport.

6. Conclusions

Today, carbon emissions from European land transportation have risen significantly above 1990 levels, making it crucial for the sector to intensify its emissions reduction efforts, especially in light of the European Green Deal (EU Commission, 2019). To achieve more targeted and effective measures to combat the sector's emissions, it is crucial to conduct empirical analysis and gain a deeper understanding of the factors that influence transport emissions in the first place. However, one important aspect that has often been overlooked in previous studies is the presence of spatial autocorrelation patterns in transport emissions. These patterns reveal how emissions tend to cluster geographically and can provide valuable insights for designing location-specific strategies to reduce carbon emissions. There is limited research available on spatial externalities in transport emissions, with the focus being mainly on China, as seen in studies by Yu et al. (2013) and Yang et al. (2019).

We advance the literature as we conduct a comprehensive analysis of carbon emissions from European land transportation, taking into account spatial autocorrelation patterns. Our research aims to find evidence of these spatial patterns and to account for them in empirical analyses, offering a more nuanced understanding of emissions in the sector. As proposed by Anselin (1988) and Anselin and Florax (1995), we make use of global and local Moran's *I* indices to verify spatial autocorrelation in the data. Additionally, in order to adequately analyze the factors influencing carbon emissions, we employ the spatial Durbin model (LeSage and Pace, 2008; Elhorst 2012; 2014) and integrate transport-specific regression models, thereby extending the classic *STIRPAT* model proposed by Dietz and Rosa (1997). The regression models include transportation parameters such as transport intensities, modal splits between road and rail, and infrastructure density. The formulation of the regression models is informed by the literature, such as Jennings et al. (2013) and Andrés and Padilla (2018). The analyses are conducted using panel data from 26 European countries between 1995 and 2019.

To our knowledge, such analysis has not been presented in the literature before. This study not only addresses existing research gaps but also has practical significance. We provide evidence of spatial dependence and spillover effects in emissions from European land transportation. This demonstrates the need for close cooperation between European countries to effectively reduce carbon emissions from land transportation. Collaboration occurs within the EU's established institutions, such as the European Parliament's Committee on Transport and Tourism and the European Environment Agency, to guide, monitor, and control reduction efforts. In addition, collaboration in smaller groups of nations with similar transport sector characteristics is recommended, and our empirical results can inform the formation of these groups. This approach can contribute to better representation of individual countries, thereby supporting the effective addressing of specific concerns and the development of customized solutions to meet their specific needs.

Our study also identifies significant factors that drive transport emissions, thereby offering valuable guidance for future policy-making aimed at promoting a more environmentally friendly and sustainable transport sector. Building on the transport activity model, we show that lowering transport intensities is a key factor in reducing transport emissions, and we observe significant spillover effects, particularly in the context of freight transportation. In addition, we find that promoting a shift from road to rail in freight transport can effectively reduce carbon emissions. Accordingly, we have briefly discussed the EU's decision to extend the ETS to include the transportation sector, which appears to be a promising measure to address both aspects effectively. Building on the transport infrastructure model, we explore direct and indirect effects from infrastructure development on transport emissions. As another key finding, we identify a non-linear relationship between infrastructure development and carbon emissions. This suggests the existence of 'sustainability sweet spots' in future infrastructure planning, emphasizing the need for infrastructure development to go beyond simply expanding the network and focus on strategic improvements.

In conclusion, this study represents pioneering work on spatial autocorrelation patterns in carbon emissions from European land transportation. With our empirical analyses, we shed light on the key areas that require particular attention in this context, such as a refined approach to cooperation among European countries. The results can advance the literature and stimulate evidence-based policy discussions among industry representatives, policymakers, and researchers, about effective strategies for decarbonizing the transport sector.

7. Limitations and future recommendations

For this empirical study, data from various sources were collected, presenting a risk of inheriting potential data errors and inconsistencies that could impact the quality of the investigation. To mitigate this risk, we have taken considerable measures to validate the data, such as reviewing the data to detect and correct inherent inconsistencies and cross-checking other sources whenever possible. Thus, we are confident that the data used in this study are reliable, enabling us to draw accurate conclusions. Another limitation of this study is that we only investigated European land transportation. Specifically, two other significant areas of the transportation sector, namely marine and aviation, were not examined in this study, despite together accounting for approximately 30% of total transport emissions in 2019 (EU Parliament, 2019). It is recommended that future research also focus on the areas of marine and aviation.

We investigated a set of influencing factors that are significant in this specific context, such as transport intensities, modal splits between road and rail, and infrastructure density. However, the overview provided by Andrés and Padilla (2018) shows that additional determinants, such as the motorization rate and private vehicle population, can also be considered when analyzing the environmental impact of transportation. Against this backdrop, our work can be regarded as a methodological blueprint, and future studies can build upon our approach by incorporating additional factors into the analyses. Our methodology can also be adapted beyond the context of transportation to examine other carbon-intensive network-based sectors, including energy, manufacturing, and agriculture. Thus, our study holds promise for informing efforts to mitigate carbon emissions across a range of industries and domains.

CRediT authorship contribution statement

Jan Sporkmann: Conceptualization, Data curation, Methodology, Writing - original draft, Writing - review & editing. **Yang Liu:** Conceptualization, Methodology, Data curation, Writing - original draft. **Stefan Spinler:** Conceptualization, Supervision.

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.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2023.103851.

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Corrigendum to "Carbon emissions from European land transportation: A comprehensive analysis" [Transport. Res. D: Transp. Environ. 121 (2023) 103851]

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The authors would like to add an introduction to the methods section "3.2. Empirical methods." In this introduction, we would like to make a reference to a paper from our co-author Yang Liu that also utilizes Moran's I indices and spatial Durbin models in the context of European energy markets and has informed our methods description (cf. Sections 3.2.1 and 3.2.2). However, the reference to this paper is missing because it was inadvertently omitted from the final revision before publication. It is important to note that the other paper was accepted for publication in the journal Energy shortly before the acceptance of our manuscript. Therefore, in order to adhere to the highest standards in scientific publications, we propose to include the following introduction in the methods section "3.2. Empirical methods":

"To analyze spatial patterns in our data, we rely upon the commonly used Moran's *I* index and the spatial Durbin model in combination with the partial derivative method. In the description of both methods, we follow the procedure presented in Liu et al. (2023) in the context of European energy markets. This communication provides a concise yet easy-to-follow way of introducing the methods."

The authors would like to apologize for any inconvenience caused.

Additional References:

Liu, Y., Xie, X., Wang, M., 2023, Energy structure and carbon emission: Analysis against the background of the current energy crisis in the EU. Energy 280, 128129.

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