Energy structure and carbon emission: Analysis against the background of the current energy crisis in the EU

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A B S T R A C T

The Ukraine war, evolving from a geopolitical crisis to an energy crisis, calls attention to understanding the impacts of restarting oil- and coal-fired power plants on carbon dioxide (CO_2) emissions. To fill the remaining research gaps relating to energy structure and CO_2 emissions in Europe, in this study, we systematically investigate the carbon emissions (CE) and their influencing factors, especially those energy-related, from 1995 to 2020. We find that European Union (EU) countries are currently at different stages of the energy transition. The CO_2 emissions in the EU show clear positive spatial dependence. Thus, we deploy the spatial Durbin model to analyze the influences of consuming coal, oil, natural gas, hydropower, solar and wind energy, nuclear power, and other renewable energy sources on CE. It is observed that natural gas is the only fossil fuel source that does not have a significant positive effect on CO_2 emissions. The developments of hydropower, nuclear power, and other renewable energy sources have significant negative impacts on CE. Estimation results of direct and indirect effects clearly show that many energy sources have spillover effects, suggesting that to fulfill future climate targets, joint-effort must be made among the EU member states.

1. Introduction

As the first international measure to address the climate change problem, the United Nations Framework Convention on Climate Change was adopted in 1992 and came into force in 1994 [1]. Since then, the adaptation of the Kyoto Protocol (KP) in 1997, the first commitment period of the KP implemented in 2008, the acceptance of the Doha Amendment in 2012, and the adoption of the Paris Agreement in 2016 show the commitment of the countries worldwide to combating climate change. The European Union (EU) has been one of the most active in reducing carbon dioxide (CO_2) emissions and promoting low-carbon and sustainable development [2]. The European Community signed the KP on April 1998, and all the 15 member countries at that time committed to an 8% cut below the 1990 emission levels [3,4]. Without counting the additional reductions from carbon sinks and international credits, the EU achieved an overall cut of 11.7% domestically in the first KP commitment period (2008–2012) [4]. In the second commitment period (2013–2020), EU countries agreed to meet a joint 20% reduction target compared to 1990, which is also in line with EU's own target set in the 2020 Climate & Energy Package [5,6]. The 2030 Climate Target Plan of the EU sets even more ambitious goals of reducing greenhouse gas (GHG) emissions to at least 55% below 1990 levels by 2030 and being climate-neutral by 2050 [7]. In Fig. 1, we present the trend of carbon emissions (CE) of the EU-28 countries from 1995 to 2020.[1]

Behind the magnificent achievement in mitigating CE, the energy transition plays a vital role, making the EU the global leader. Two important pillars of the energy transition in the EU are the reduction in fossil fuel consumption and the promotion of renewable energy (RE) sources [9]. In 2020, the EU successfully increased the share of RE to over 22.10% of the total consumption, beyond its 20% headline target [10]. Germany, as a pioneer in coal phase-out and RE development, actively advances the energy transition by, on the one hand, closing down the coal-fired power stations progressively and, on the other hand, issuing a series of the Renewable Energy Sources Act amendments to promote the production of RE [11–14]. Similarly, in 2006, the prime minister of Denmark announced the long-term target: 100% independency of fossil fuels and nuclear power and 100% RE systems [15]. Other countries, such as Italy, Sweden, Austria, Belgium, Portugal, among others, have also issued policies to achieve their goals of de-carbonization and RE promotion [16–20]. As stated by Eyl-Mazzega

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[1] The EU-28 countries are the current 27 EU member states and the United Kingdom.

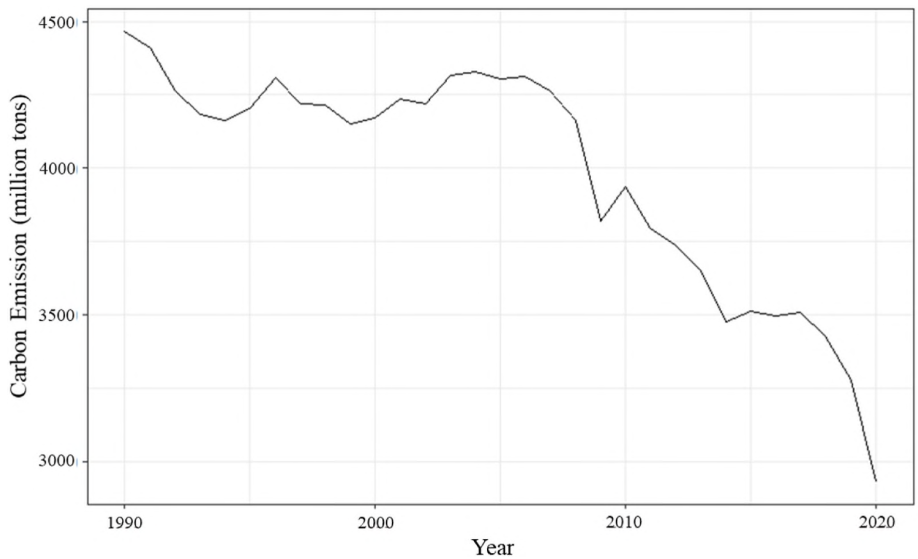

Fig. 1. Total Carbon Emission of the 28 EU Countries from 1995 to 2020. Note: The data is collected from Ritchie et al. (2020) [8].

(2020), the current EU energy policy is a de-carbonization policy with several goals: de-carbonization and competitive, secure, and integrated energy markets [21]. However, the current Russia's invasion of Ukraine raises questions about how secure is the EU energy policy and what will be the environmental consequences of this war.

Since the beginning of the Ukraine war, Russia has reduced natural gas (NG) deliveries to Europe, making the Ukraine crisis from a geopolitical crisis to an energy crisis. As argued by Mata Pérez et al. (2019), the energy situations of the EU member states vary significantly due to the differences in geography, natural resources, history, and political traditions. Countries in Eastern Europe are deeply concerned about the security of energy supply, particularly the NG, as these countries are characterized by a high level of import dependence combined with strong market concentration, and often have a single supplier: Russia [22]. In addition, these countries generally have a high share of fossil fuels in their energy consumption and a less diversified energy structure. For instance, unlike other major coal producers in the EU, e.g., the United Kingdom (UK), Germany, Spain, etc., which have already stopped black coal mining, Poland has just committed itself in 2021 to end coal production by 2049 [23]. Besides, the options for diversifying, in terms of source, origin and route, are highly constrained in the short- and even medium-term. Furthermore, the development of RE sources in these countries also lags behind those in the western part of the continent due to the natural conditions and political obstacles [24]. Thus, the current energy crisis hits these countries the most. Consumers in these countries have less disposable income, so they tend to be more sensitive to changes in energy prices, making the increment of coal and oil in total energy consumption the only way to get through the current energy difficulties [25].

Countries in Western Europe generally have more diversified energy structures and have promoted the renewable and clean energy (RECE) production for a long time. Besides, these countries have already improved their energy import dependence [22]. While the share of coal has decreased in the energy structure, the proportion of the NG has steadily increased across these countries over the past decades [26]. According to the Eurostat, in 2021, EU's 39.70% imported NG were from Russia, followed by Norway, Algeria, and the United States (US) with 24.90%, 8.20%, and 7.20%, respectively. However, in the second quarter of 2022, when the Ukraine war began, the share of Russia decreased to 22.90%, leaving a vast gas supply gap [27]. Other suppliers have already increased their gas export to the EU, such as the US [27]. However, the gap remains. Thus, facing the current energy crisis, countries like Austria, Denmark, France, and Germany still have to reactivate their coal- or oil-fired power plants to compensate for the energy gap left by Russia [28–31].

Against this background, the question about the impacts of restarting the oil- and coal-fired power plants and the shrinking share of NG in total energy consumption on CE in the EU is raised. In the literature, there are only a few studies focusing on the energy structure and CO_2 emissions in the EU. One of the first studies was conducted by Bölük and Mert (2014), who found that RE consumption contributes around 50% less per unit GHG than fossil energy in EU countries [32]. Dogan and Seker (2016) investigated the influences of non- and renewable energy sources on European CO_2 emissions [33]. Similar research was conducted by Bekun et al. (2019), who adopted a different method to study 16 EU countries [34]. Neagu and Teodoru (2019) examined the effect of non-renewable energy consumption on CE [35]. Ren et al. (2021) studied the impacts of consuming NG and RE on CE in the EU [36]. Shahnazi and Shabani (2021) reported a negative effect of RE on CO_2 emissions [37]. Using panel spatial simultaneous equations models, Radmehr et al. (2021) explored the linkage between CE and RE consumption in the EU. They reported a one-way relationship from RE to CO_2 emissions [38]. However, going through the literature, it is found that these studies either did not account for the spatial pattern of the CO_2 emissions or distinguish between different types of traditional and RE sources. Thus, the effect of each individual energy source, e.g., coal, oil, and NG in the fossil fuel category and hydropower, nuclear power, solar and wind energy in the RECE group, is still not investigated. In particular, against the current Ukraine war background, it is vital to understand the impacts of increasing shares of coal and oil in total energy consumption on CO_2 emissions in the EU.

To address this research gap, in this study, we systematically investigate the impacts of three fossil fuel energy sources, i.e., coal, oil, and NG, and four RECE sources, i.e., hydropower, solar and wind energy, nuclear power, and other RE sources, on CO_2 emissions in 26 EU countries from 1995 to 2020.[2] It is found that the studied EU countries are currently in different phases of the energy transition. A clear difference between old and new EU member countries in their energy structures is identified. As noted by Dogan and Seker (2016), many studies related to CO_2 emissions use panel methods that ignore cross-sectional dependence [33]. Thus, in this study, we adopt the global Moran's I index test to first examine the spatial pattern of the CE and then adopt the spatial Durbin model (SDM) to

[2] The 26 countries are the UK and the current EU 27 countries, excluding Malta and Cyprus.

account for the spatial dependence when investigating CE influencing factors. We find that CE has a positive spatial autocorrelation pattern from 1995 to 2020, and the strength of the dependence is strongly affected by economic and political events. Controlled for population, affluence and technological progress, the estimation results of the SDM indicate that the consumption of coal and oil positively affects CO_2 emissions, while NG is carbon-neutral. Our direct and indirect effects estimation further implies that hydropower, nuclear power, and other RE sources can either directly or indirectly influence CE in a negative way, while solar and wind energy does not have a significant impact on CO_2 emissions in the EU.

The remainder of the paper is organized as follows. In the next section, we describe the sample data and the methodologies. We report our empirical results in the third section. In the fourth section, we discuss the key findings of this research. We conclude this study in the last section.

2. Methodology and data

2.1. Methodology

2.1.1. Spatial dependence analysis

To test the spatial pattern of the CO_2 emissions in the EU, we deploy the global Moran's I index test. As an index test, the calculation formula of the global Moran's I index is commonly defined as follows:

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

$$\text{with } S^2 = \frac{\sum_i (z_i - \bar{z})^2}{n} \text{ and } w_{ij} = \begin{cases} 1, \textit{if areas i and j are adjacent} \\ 0, \textit{otherwise} \end{cases}, \tag{1}$$

where z_i and z_j are the observed values of regions i and j. $\bar{z}$ denotes the sample average. w_{ij} is the ith, jth element of a spatial weight matrix W, which specifies the degree of dependence between regions i and j. $w_{ij} = 1$, when i and j are neighboring regions, and $w_{ij} = 0$, when regions i and j are not adjacent.[3] The hypothesis test of the global Moran's I index is defined as follows:

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

$$\text{with } I_0 = E(I). \tag{2}$$

The global Moran's I index has a value range from -1 to 1. The null hypothesis is that there is no spatial autocorrelation. A significant positive global Moran's I index $I > I_0$ is the signal of the spatial clustering phenomenon, while the negative one $I < I_0$ implies a spatial dispersion situation [39].

2.1.2. Spatial durbin model

In general, there are three spatial models used to analyze the inner mechanism of spatial correlation, i.e., the spatial autoregressive model (SAR), the spatial Durbin model (SDM), and the spatial error model (SEM) [40]. We start with a universal model, defined as follows:

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

$$\text{with } w_{ij} = \begin{cases} 1, \textit{if areas i and j are adjacent} \\ 0, \textit{otherwise} \end{cases} \text{ and } \varepsilon_{it} = \gamma \sum_{j=1}^{n} w_{ij} \varepsilon_{it} + \varepsilon_{it}, \tag{3}$$

where i and j denote regions i and j, respectively, and t represents year t. Y is an $N \times 1$ matrix of the dependent variable, and X 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 and θ are the coefficients of the independent and spatial lag independent variables to be estimated. α is a constant, and ε is a random error term with an independent and identical distribution [41]. When $\gamma = 0$ and $\theta = 0$, Eq. (3) is reduced to SAR defined as follows:

$$Y_{it} = \alpha + \rho \sum_{j=1}^{n} w_{ij} Y_{it} + \varphi X_{it} + \varepsilon_{it}$$

$$\text{with } w_{ij} = \begin{cases} 1, \textit{if areas i and j are adjacent} \\ 0, \textit{otherwise} \end{cases}, \tag{4}$$

the SAR assumes that the autoregressive process is only on the dependent variable Y [42,43]. When in Eq. (3) $\rho = 0$ and $\theta = 0$, the model is the SEM defined as follows [44]:

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

$$\text{with } w_{ij} = \begin{cases} 1, \textit{if areas i and j are adjacent} \\ 0, \textit{otherwise} \end{cases} \text{ and } \varepsilon_{it} = \gamma \sum_{j=1}^{n} w_{ij} \varepsilon_{it} + \varepsilon_{it}. \tag{5}$$

When $\gamma = 0$, Eq. (3) is reduced to the SDM, which is derived as follows:

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

$$\text{with } w_{ij} = \begin{cases} 1, \textit{if areas i and j are adjacent} \\ 0, \textit{otherwise} \end{cases}, \tag{6}$$

the SDM contains both the spatial lag terms of the dependent variable Y and the independent variables X [45]. Furthermore, as the SDM deals with panel data, it is sometimes necessary to control the individual and time effects in the data. Thus, μ and λ representing the individual effect and the time effect can be added to the model, leading to the individual and time fixed effects SDM as follows:

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

$$\text{with } w_{ij} = \begin{cases} 1, \textit{if areas i and j are adjacent} \\ 0, \textit{otherwise} \end{cases}. \tag{7}$$

The SDM allows researchers to examine the indirect effect, i.e., impacts to or from neighboring counties, by interpreting the estimates on spatial lag independent variables [46]. However, using the SDM to test whether a variable has a spillover effect is likely to result in biased findings [47]. Thus, we adopt the partial derivative method to estimate the direct and indirect effects based on the SDM estimation [44,47]. As the starting point, the SDM can be rewritten as follows:

$$Y_t = (I_n - \rho W)^{-1}\alpha + (I_n - \rho W)^{-1} X\varphi + (I_n - \rho W)^{-1} WX\theta + (I_n - \rho W)^{-1}\varepsilon, \tag{8}$$

where I_n is an $N \times K$ identity matrix. The partial derivatives of the dependent variable Y relative to the kth explanatory variable X_k across the n observations can be then expressed as follows:

$$\begin{bmatrix} \frac{\partial Y}{\partial X_{1k}} & \cdots & \frac{\partial Y}{\partial X_{Nk}} \end{bmatrix} = (I_n - \rho W)^{-1}[\varphi_k I_n + \theta_k W]. \tag{9}$$

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.

2.2. Data and model specification

Considering CO_2 as a pollutant, the CO_2 emissions can be calculated by employing the classic *IPAT* model, which is illustrated as follows [48]:

[3] In in the spatial weight matrix, we set the UK adjacent to France as these two countries are connected via road traffic.

$$I = P \times A \times T, \quad (10)$$

where I indicates the pollution, i.e., CO_2 emissions, P is the total population, A is the affluence, and T is the level of technological development [49]. However, as a mathematical formula, the *IPAT* model assumes that the elasticities of population, affluence, and technology on environment change are unity, which is, however, in conflict with the Environmental Kuznets Curve (EKC) hypothesis [49–51]. Thus, we adopt the *STIRPAT* model proposed by Dietz and Rosa (1997), which is a stochastic version of the *IPAT* model [52]. This model can be written in a simplified way as follows [49]:

$$I_t = \alpha + \beta_1 P_t + \beta_2 A_t + \beta_3 T_t + \varepsilon_t, \quad (11)$$

where I, P, A, and T are the same as in the *IPAT* model, and α and ε are the intercept and the random error term, respectively. Based on the *STIRPAT* model, Xu and Lin (2017) reported that energy structure is a critical driving factor of CO_2 emissions [48,52]. It brings us to specify our model as follows:

$$CPC_t^i = \alpha + \beta_1 POP_t^i + \beta_2 GDP_t^i + \beta_3 ENI_t^i + \beta_4 ENS_t^i + \varepsilon_t, \quad (12)$$

CPC_t^i is the per-capita CO_2 emissions (ton) in country i in year t [8].[4] POP_t^i and GDP_t^i are the population size (thousand people) and GDP per capita (USD 2015 price) in country i in year t [53]. We use the energy intensity, ENI_t^i (kilograms of oil equivalent/thousand Euro), i.e., for one thousand Euro GDP, how many kilograms of oil equivalent are consumed, to proxy the technological development [54,55]. ENS_t^i denotes the energy structure in country i in year t, defined as the shares of different energy sources in the total primary energy consumption using the substitution method.[5] In this study, we study three traditional energy sources, i.e., coal (*COL*), oil (*OIL*), and NG (*NGS*), and four RECE sources, namely hydropower (*HYE*), solar and wind energy (*SAW*), nuclear power (*NCR*) and other RE sources (*RNE*), e.g., biomass. A detailed description of the collected data can be found in the Supplementary Material [56].

Taking the natural logarithm to eliminate possible heteroscedasticity, our model can also be written as follows:

$$\begin{aligned} log\left(CPC_t^i\right) = &\alpha + \beta_1 log\left(POP_t^i\right) + \beta_2 log\left(GDP_t^i\right) + \beta_3 log\left(ENI_t^i\right) + \beta_4 log\left(COL_t^i\right) \\ &+ \beta_5 log\left(OIL_t^i\right) + \beta_6 log\left(NGS_t^i\right) + \beta_7 log\left(HYE_t^i\right) + \beta_8 log\left(SAW_t^i\right) \\ &+ \beta_9 log\left(NCR_t^i\right) + \beta_9 log\left(RNE_t^i\right) + \varepsilon_t. \end{aligned} \quad (13)$$

The descriptive statistics and the correlation matrix for all the constructed variables for 26 studied countries from 1995 to 2020 are reported in Table 1. To enhance the credibility of the regression estimation, we conduct the panel data stationarity test for each of the studied variables to rule out the potential spurious regression. Since the panel unit root test requires excluding countries with all the observations of zero throughout the studied period from the sample, it could sometimes lead to a panel of fewer than 26 countries (N) for 26 years (T), i.e., a small N and large T pattern. Based on this, we select the unit root test method proposed by Maddala and Wu (1999) to test the stationarity of the variables [57].

As listed in Table 2, the unit root test results indicate that all the derived variables are stationary either with drift, around trend, or in both models. Furthermore, we deploy the variance inflation factor test to detect the multi-collinearity problem in our specified model. The results in Table 3 clearly show that all the variance inflation factors are less than the conventional threshold of ten, implying that our model does not have multi-collinearity problem.

3. Empirical results

3.1. Energy structure development in the EU

In Table 4, we list the EU-level shares of different energy sources in total primary energy consumption in 1995 and 2020 and compare them using the *t*-test. The average share of coal decreased from 22.97% in 1995 to 10.88% in 2020. The difference is tested to be significant. Regarding oil consumption, we observe a downward trend during this period. However, the difference is nonsignificant. The only energy source in the fossil fuel category showing increasing consumption is the NG, which increased from 18.79% to 21.68% throughout the studied period. Regarding the RECE group, only the share of nuclear power decreased slightly from 9.35% to 8.24%. The proportions of solar and wind energy and other RE sources had significant increments from 1995 to 2020, while there was no significant change in the share of hydropower during this period. In Fig. S1 in the Supplementary Material, we plot the trends of these seven energy sources from 1995 to 2020.

In Figs. 2–5, we provide maps of the focused 26 EU countries to illustrate the changes in shares of coal, oil, NG, and total RECE, i.e., the sum of the shares of hydropower, solar and wind energy, nuclear power, and other RE sources, from 1995 to 2020. As displayed in Fig. 2, compared to countries in Eastern Europe, countries in the western part of the continent generally had smaller shares of coal in their total primary energy consumption in 2020. In terms of oil, we observe in Fig. 3 that in 1995, countries in Western Europe had higher proportions of oil in their energy structures. During the studied period, almost all the studied countries reduced their oil shares. In Fig. 4, we observe an increasing trend of NG proportion in most of these countries. Countries in the middle and eastern parts of the continent had, on average, larger shares of NG in their energy structures. In Fig. 5, we illustrate the development of RECE sources in 1995 and 2020. In 2020, new EU member countries generally had smaller shares of RECE in their primary energy structures than old member states. In addition, the remarkably large share of RECE in France is mainly due to the high proportion of nuclear power in total energy consumption. In Supplementary Material Figs. S2–S5, we provide similar maps for the four RECE sources, respectively. Furthermore, in Table S2 in Supplementary Material, we provide an overview of the energy structure for each studied country.

3.2. Spatial dependence test

Table 5 lists the results of the global Moran's I index test, which examines the overall spatial autocorrelation pattern of all the studied countries. As shown, the global Moran's I index values are positive over the studied period. In 21 out of the total 26 years, we identify significantly positive CE autocorrelation of the studied countries. Similar results are obtained in other countries, such as China and the US, where positive province- and state-level spatial dependence in CO_2 emissions was observed [57–62]. Our finding provides evidence that CE in one country might be affected not only by local factors but also by surrounding environments. Besides, the significantly positive Moran's I index implies the potential spatial agglomeration feature of the CO_2 emissions in the EU, namely high CO_2 per capita countries tend to be distributed together [63]. In Supplementary Material, we further report the results of the local Moran's I index test.

In Fig. 6, we plot the global Moran's I values. As shown, from 1995 to 2000, there was a clear upwards trend in the spatial dependence, indicating that in this period, there was a strong spatial dependence in the CO_2 emissions among the studied countries. Starting from 2000, the spatial dependence of the CE tended to be weaker. A clear decreasing trend in spatial dependence is observed during this period. Beginning in

[4] The data on CO_2 emissions measures the emissions from the burning of fossil fuels, and directly from industrial processes such as cement and steel production. Emissions from land use change, deforestation, soils, or vegetation are not included.

[5] In the Supplementary Material, we provided detailed explanation of the substitution method.

Table 1
Descriptive statistics and correlation matrix.

	POP	GDP	ENI	COL (%)	OIL (%)	NGS (%)	HYE (%)	SAW (%)	NCR (%)	RNE (%)
Panel A: Descriptive Statistics										
Minimum	408.60	3537.11	44.23	0.66	16.28	0.00	0.00	0.00	0.00	0.00
Median	10,244.23	18,250.07	169.86	13.79	37.34	21.13	3.59	0.64	5.05	0.94
Mean	21,510.25	26,165.38	216.41	17.99	39.73	21.68	6.86	2.32	9.17	1.80
Maximum	83,166.71	112,417.90	868.39	73.77	74.68	48.61	36.34	26.39	42.20	12.87
Std. Dev.	23,377.45	21,195.51	133.87	15.96	13.01	10.65	8.41	3.71	10.98	2.32
Panel B: Correlation Matrix										
POP	1.00									
GDP	0.03	1.00								
ENI	−0.56	−0.31	1.00							
COL	−0.32	−0.08	0.51	1.00						
OIL	0.48	−0.06	−0.53	−0.5	1.00					
NGS	−0.03	0.14	−0.04	−0.35	0.06	1.00				
HYE	−0.18	−0.12	−0.10	−0.34	−0.10	−0.26	1.00			
SAW	0.26	0.09	−0.39	−0.18	0.11	−0.04	−0.09	1.00		
NCR	−0.10	0.11	0.21	−0.16	−0.44	−0.27	0.09	−0.21	1.00	
RNE	0.26	−0.05	−0.30	−0.11	−0.13	−0.22	0.18	0.43	0.019	1.00

Note: Std. Dev. Stands for standard deviation.

Table 2
Results of the unit root test.

	Intercept		Intercept and Trend	
	χ^2	*p*-Value	χ^2	*p*-Value
log*(POP)*	108.81***	0.0000	40.68	0.8719
log*(GDP)*	81.85***	0.0052	240.86***	0.0000
log*(ENI)*	20.68	0.9999	120.62***	0.0000
log*(COL)*	42.40	0.8265	71.51**	0.0376
log*(OIL)*	94.63***	0.0003	160.97***	0.0000
log*(NGS)*	88.86***	0.0011	94.22***	0.0003
log*(HYE)*	338.58***	0.0000	440.97***	0.0000
log*(SAW)*	12.26	0.9999	71.97**	0.0347
log*(NCR)*	48.78**	0.0165	99.22***	0.0000
log*(RNE)*	39.61	0.8964	124.11***	0.0000

Note: The null hypothesis of the stationarity test is that there is a unit root in the time series. The optimal lag length is selected using Schwarz information criterion. ***, ** and * denote the significance at the levels of 1%, 5% and 10%, respectively.

Table 3
Results of the variance inflation factor test.

Variable	VIF	Variable	VIF	Variable	VIF
log*(POP)*	4.84	log*(GDP)*	1.68	log*(ENI)*	7.34
log*(COL)*	2.15	log*(OIL)*	3.19	log*(NGS)*	1.63
log*(HYE)*	1.98	log*(SAW)*	1.95	log*(NCR)*	1.85
log*(RNE)*	1.70				

Note: This table reports the variance inflation factor test results for the variables in the regression models.

Table 4
Changes in average Shares of Energy Sources in total Primary Energy Consumption from 1995 to 2020.

	Total Sample (%)	2020 (%)	1995 (%)	Difference (%)	t-Statistic
COL	17.99	10.88	22.97	−12.09***	−2.78
OIL	39.73	37.48	41.28	−3.80	−1.06
NGS	21.68	23.13	18.79	4.34	1.44
HYE	6.86	7.11	7.00	0.11	0.04
SAW	2.32	7.81	0.07	7.74***	6.61
NCR	9.17	8.24	9.35	−1.11	−0.37
RNE	1.80	4.02	0.53	3.49***	5.49

Note: ***, **, and * denote the significance at the levels of 1%, 5%, and 10%, respectively.

2008, the global Moran's *I* values started to fluctuate at a relatively low level, implying a moderate spatial dependence of the emitted CO_2 in these European countries.

The results of the CE spatial dependence test suggest adopting the spatial panel data model to account for the spatial pattern in the data, leading us to choose our model among the SAR, SDM, and SEM. In addition, it is necessary to examine whether it is necessary to fix individual and time effects in our selected model.

3.3. Spatial durbin model estimation

To understand which spatial model fits our data the most and whether it is necessary to fix both individual and time effects in our selected spatial model, we first use the non-spatial models for the estimation. In Table 6, we list the regression results using the pooled ordinary least square model (OLS), the panel data random effects model (PRE), the individual fixed effects model (SFE), the time fixed effects model (TFE), and the individual and time fixed effects model (STF). Furthermore, we report the results of the log-likelihood, likelihood ratio (LR) test, Durbin-Wu-Hausman test (Hausman test), and Lagrange multiplier (LM) test for both spatial lag and error for each of the above-mentioned models [63–65]. Based on the results of these tests, we select the model that suits the best.

As reported in Table 6, the results of the LR test imply that compared to the OLS model, the PRE, SFE, TFE, and STF models have a better fit. Besides, the results of the Hausman test that helps us determine whether it is more suitable to use the random or the fixed effects models to investigate our data indicate the superiority of the fixed effects models. Based on the results of log-likelihood, LR, and Hausman tests, it is evident that the model deployed in our analysis should fix both individual and time effects, leading us to the STF model. Since the existence of spatial dependence is evident, we further examine whether it is necessary to include both the spatial lag dependent variable (LM spatial lag) and spatially autocorrelated error term (LM spatial error) in our selected STF model. As shown in Table 6, the test statistics of both the LM spatial lag and error and the robust LM spatial lag and error in the STF model are significant, indicating that both SAR and SEM models are accepted. According to Lesage and Pace (2009), in such circumstances, the SDM should be employ. Based on all these test results, we deploy the SDM with spatial and time-fixed effects for our analysis [44,62].

In Table 7, we report the estimation results of our individual and time fixed effects SDM. As mentioned beforehand, the interpretation of the direct and indirect effects based on the SDM might be misleading. Thus, we only focus on the sign and significance of the SDM. The factor loading on *POP* is positively significant at the 1% level. This finding implies that there is no so-called economies of scale effect existing in the

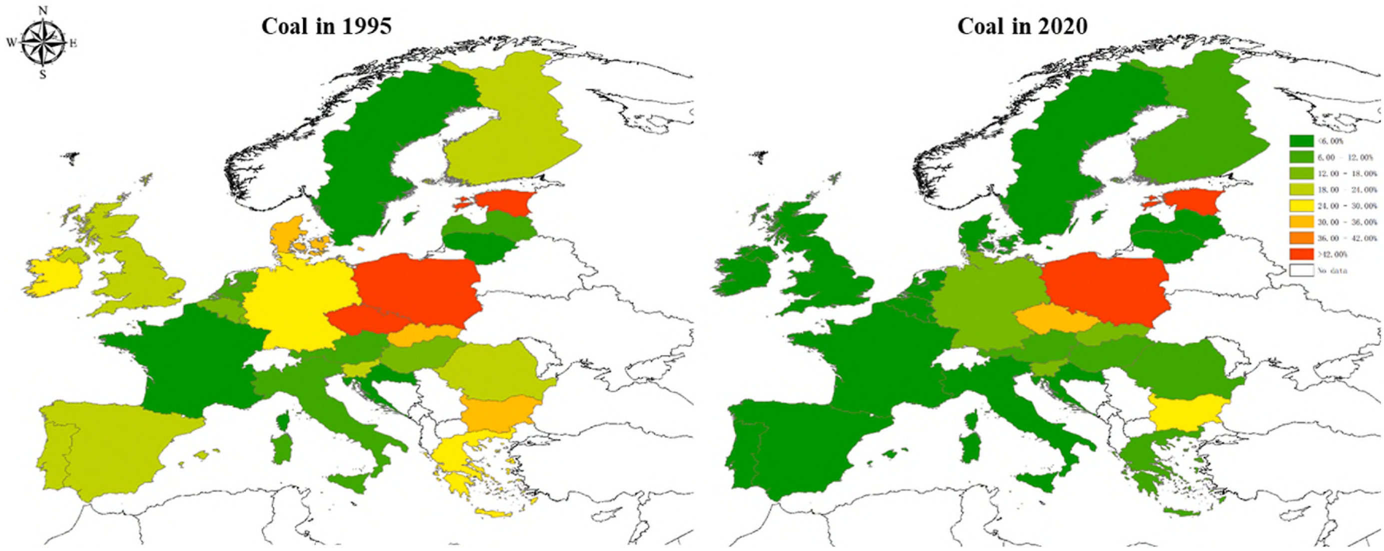

Fig. 2. Share of Coal in total Primary Energy Consumption in 1995 and 2020.

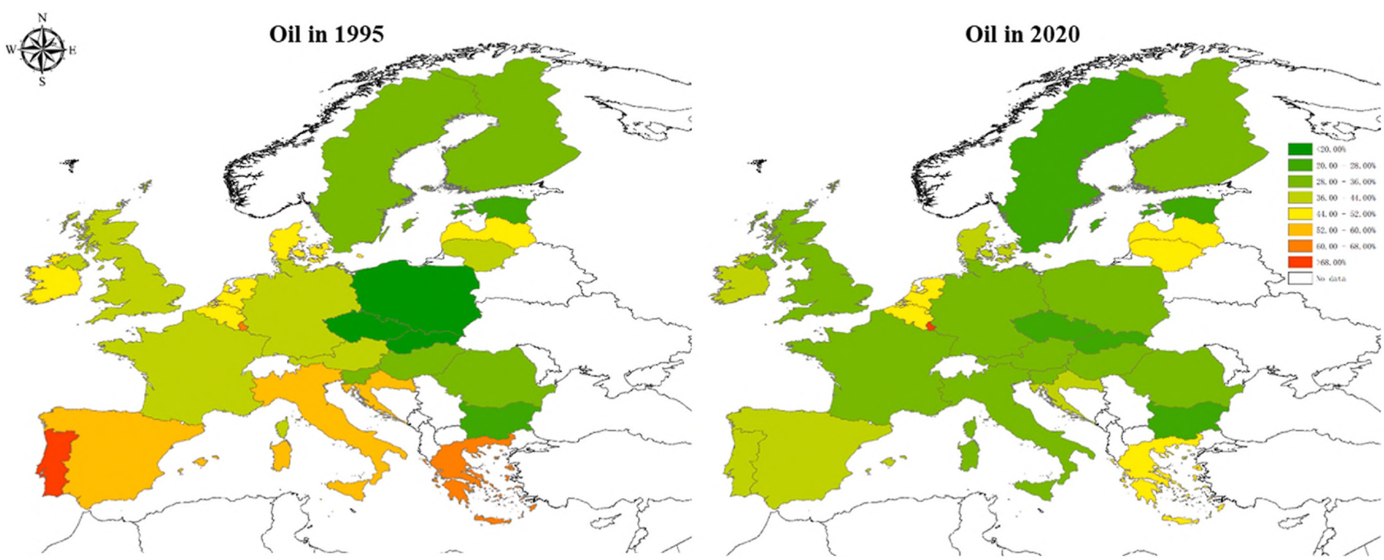

Fig. 3. Share of the Oil in total Primary Energy Consumption in 1995 and 2020.

CO_2 emissions in the studied EU countries as there is no marginal decrease in the per-capita CE with increasing population size. The coefficient on spatial lag *POP* also passes the 10% significance level, implying that population size has a significant spillover effect on CO_2 emissions in neighboring countries. In contrast, the factor loadings on *GPD* and spatial lag *GDP* are negative and significant at the 1% level. It implies that further economic growth is correlated with a decrease in CO_2 per capita domestically and in adjacent countries. As expected, as an inefficiency measure, the energy intensity, *ENI*, is observed to be positively related to CE, indicating that technological development can significantly reduce the CO_2 emissions. Regarding the energy structure, it is found that coal has both significant direct and spillover effects. It is worth noting that the nature of these two effects is different. The factor loading on *OIL* is observed to be nonsignificant at the conventional level. In contrast, the coefficient on spatial lag *OIL* is found to be positive and significant at the 1% level. Despite its fossil fuel nature, the coefficients on *NGS* and spatial lag *NGS* are both nonsignificant, indicating no influence from further consumption of NG on CE. Regarding the RECE sources, it is observed that hydropower is negatively correlated with domestic CO_2 emissions, and this relationship is statistically significant. Surprisingly, we do not find any reliable relation between CE and the consumption of solar and wind energy. In contrast, the factor loadings on *NCR* and *RNE* and spatial lag *NCR* and *RNE* are negative and significant at the 1% level, implying direct and indirect relationships exist between nuclear power and other RE sources and CE.

In Table 7, we also list the estimated direct and indirect effects of each variable in the SDM. In general, the estimated direct and spillover effects are in line with the estimation results of SDM; only the impact magnitude varies slightly. In the fossil fuel category, since we have a log-log model, the factor loadings on coal can be interpreted as 1% increase of coal share in the whole energy structure is correlated with, on average, 0.0521% local increment and 0.0527% inter-regional decline of the CO_2 emissions, respectively. Oil only has a significant spillover effect in that 1% increment of oil consumption is related to, on average, a 0.0460% increase in CE in adjacent countries. In the RECE group, 1% further consumption of hydropower, nuclear power, and RE is related to 0.0673%, 0.0721%, and 0.0254% decrease in domestic per-capita CO_2 emissions, respectively. Regarding the spillover effect, nuclear power and RE have significant and negative effects on CO_2 emissions in adjacent countries.

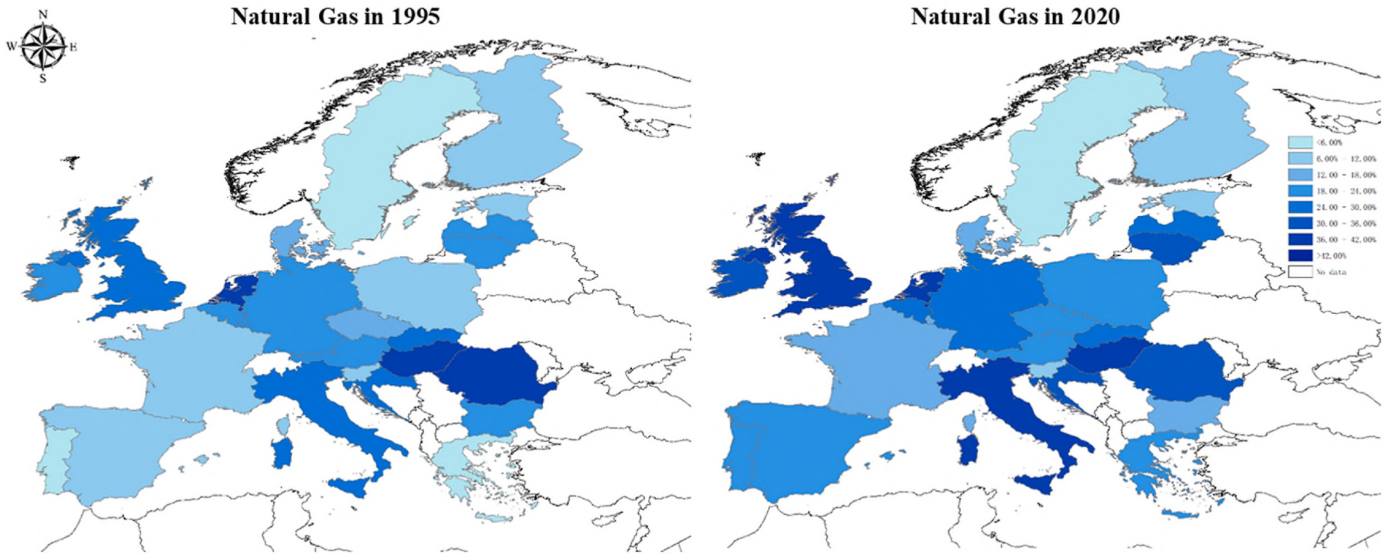

Fig. 4. Share of Natural Gas in total Primary Energy Consumption in 1995 and 2020.

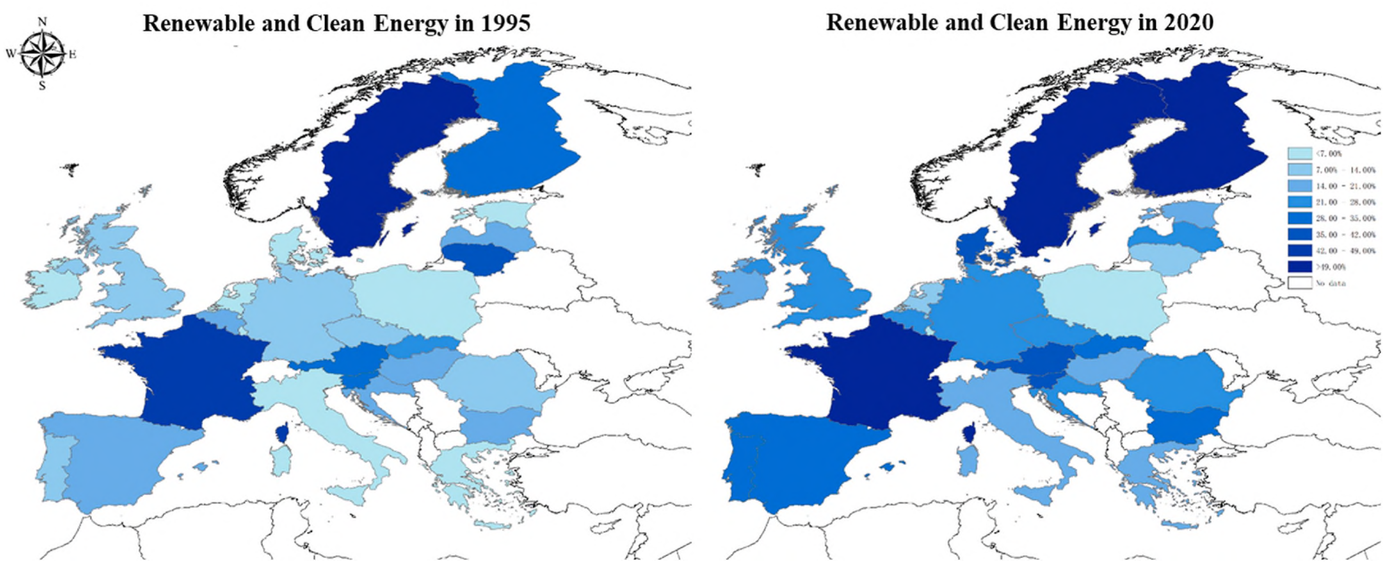

Fig. 5. Share of the Renewable and Clean Energy Sources in total Primary Energy Consumption in 1995 and 2020.

Table 5
Global Moran's *I* index for EU carbon emissions.

Year	*I*	*p*-value	Year	*I*	*p*-value
1995	0.3003**	0.0207	2008	0.1673	0.1049
1996	0.3080**	0.0192	2009	0.2110*	0.0643
1997	0.2815**	0.0280	2010	0.2359**	0.0489
1998	0.3228**	0.0156	2011	0.1664	0.1062
1999	0.3309**	0.0133	2012	0.1851*	0.0870
2000	0.3389**	0.0115	2013	0.2237*	0.0574
2001	0.3193**	0.0156	2014	0.1886*	0.0853
2002	0.3108**	0.0172	2015	0.1994*	0.0765
2003	0.2716**	0.0303	2016	0.1806*	0.0952
2004	0.2520**	0.0378	2017	0.1293	0.1564
2005	0.2220*	0.0540	2018	0.1514	0.1267
2006	0.2001*	0.0720	2019	0.2109*	0.0654
2007	0.1394	0.1393	2020	0.2180*	0.0613

Note: ***, **, and * denote the significance at the levels of 1%, 5%, and 10%, respectively.

4. Discussion

Our research yields many valuable insights. In this section, we discuss the key findings of our study. First, the results of the global Moran's *I* index test indicate that, in general, there is a significantly positive spatial dependence in CO_2 emissions among the focused countries from 1995 to 2020. This observation provides evidence that mature business and industrial cluster exists in the EU zone. When plotting the values of the global Moran's *I* index, it is found that the strength of the spatial dependence changes over time. In Fig. 7, we plot the Moran's *I* index values and mark some important events during this period. As shown, during the 2007–2008 Global Financial Crisis, the spatial autocorrelation is tested to be nonsignificant. Similarly, during the European Debt Crisis and post-BREXIT period, the values of Moran's *I* index do not pass the 10% significant level. This observation suggests that the spatial dependence of CE in the EU is closely correlated with global and continental events.

Another important finding is that population size has a significantly positive effect on CE, while the influence of affluence proxied by GDP

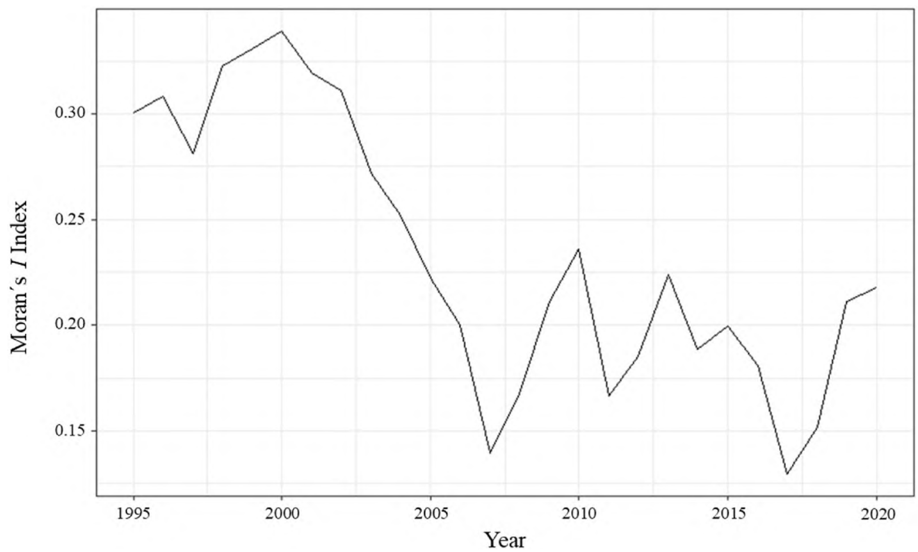

Fig. 6. Plot of Global Moran's *I* index.

Table 6
Results of non-spatial model estimations.

	OLS	PRE	SFE	TFE	STF
Intercept	1.4400**	−6.7298***			
	(0.6216)	(0.6325)			
log(*POP)*	0.1767***	0.5301***	0.5203***	0.1686***	0.4688***
	(0.0258)	(0.0285)	(0.0286)	(0.0265)	(0.0310)
log(*GDP)*	−0.0507***	−0.0686**	−0.3371***	−0.0537***	−0.3856***
	(0.0090)	(0.0307)	(0.0539)	(0.0093)	(0.0585)
log(*ENI)*	−0.2308***	0.6583***	0.6708***	−0.2480***	0.5871***
	(0.0469)	(0.0402)	(0.0396)	(0.0481)	(0.0409)
log(*COL)*	0.1919***	0.0996***	0.0792***	0.1894***	0.0635***
	(0.0139)	(0.0099)	(0.0101)	(0.0145)	(0.0103)
log(*OIL)*	0.1104**	0.1300***	0.1078***	0.0921*	0.1131***
	(0.0492)	(0.0367)	(0.0359)	(0.0518)	(0.0361)
log(*NGS)*	−0.0162	0.0697***	0.0632***	−0.0143	0.0416***
	(0.0158)	(0.0114)	(0.0111)	(0.0162)	(0.0118)
log(*HYE)*	−0.1283***	−0.0498***	−0.0609***	−0.1297***	−0.0574***
	(0.0114)	(0.0156)	(0.0161)	(0.0116)	(0.0163)
log(*SAW)*	−0.2434***	−0.0696***	−0.0620***	−0.2343***	−0.0299***
	(0.0163)	(0.0085)	(0.0083)	(0.0202)	(0.0100)
log(*NCR)*	−0.0060	−0.0583***	−0.0582***	−0.0054	−0.0583***
	(0.0088)	(0.0085)	(0.0083)	(0.0089)	(0.0080)
log(*RNE)*	0.0423**	−0.0230**	−0.0290***	0.0497**	−0.0155
	(0.0196)	(0.0096)	(0.0094)	(0.0205)	(0.0098)
Log-Likelihood	18.24	846.36	886.80	22.48	931.85
LR Test		1656.20***	1737.10***	8.49	1827.20***
Hausman Test			7.76	753.22***	88.71***
LM Spatial Lag					4.06**
Robust LM Spatial Lag					35.29***
LM Spatial Error					4.62**
Robust LM Spatial Error					35.85***

Note: This table presents the non-spatial model estimation results. Besides the log-likelihood, we report the results of the LR test, in which the OLS is the benchmark model. The results of the Hausman test are also presented, in which the PRE serves as the benchmark model. Furthermore, we list the results of the LM tests for spatial lag and error and robust spatial lag and error. The standard errors for the estimated coefficients are reported in parentheses. ***, ** and * denote the significance at the levels of 1%, 5% and 10%, respectively.

per capita is negative. In line with Dietz and Rosa (1997), our results suggest that, for countries with large population sizes, there is diseconomies of scale effect in the CO_2 emissions [52]. Similar findings are obtained in previous studies, such as Dong et al. (2018), who examined 128 countries and reported a positive and significant influence of population size on CE [66]. Regarding the impact of GDP on CO_2 emissions, both direct and spillover effects are negative. Previous studies in China, Malaysia, the Middle East, and North African countries, among others, generally reported a statistically positive relationship between CO_2 emissions and economic growth [48,66,67]. However, the affluence levels of these countries are generally lower than the studied 26 EU countries. Thus, consistent with the assumptions of the *STIRPAT* model, our results imply that real GDP per capita increases CE until some threshold level of affluence is reached, after which CO_2 emissions begin to decline [68,69]. Furthermore, the implied inverted U-shape affluence impact on CE supports the validity of the EKC hypothesis in the EU [70].

As listed in Tables 4 and 7, compared to the other two fossil fuel sources, NG is tested to be CO_2-neutral and took, on average, a share of 23% of the total energy consumption in the EU in 2020. However, the current Ukraine war poses uncertainty over the supply of NG. According

Table 7
Estimation results of the spatial Durbin model and direct and indirect effects.

	SDM		Direct Effects	Indirect Effects
	Independent Variables	Spatial Lag Variables		
log(*CPC*)		−0.0116		
		(0.0321)		
log(*POP*)	0.5082***	0.0406*	0.5037***	0.0410**
	(0.0290)	(0.0211)	(0.0287)	(0.0203)
log(*GDP*)	−0.1581***	−0.3038***	−0.1504***	−0.3023***
	(0.0558)	(0.0328)	(0.0555)	(0.0345)
log(*ENI*)	0.7373***	−0.0152	0.7265***	−0.0141
	(0.0387)	(0.0286)	(0.0371)	(0.0286)
log(*COL*)	0.0515***	−0.0536***	0.0521***	−0.0527***
	(0.0094)	(0.0065)	(0.0086)	(0.0063)
log(*OIL*)	0.0421	0.0474**	0.0382	0.0460***
	(0.0335)	(0.0201)	(0.0359)	(0.0180)
log(*NGS*)	−0.0013	−0.0106	−0.0007	−0.0112
	(0.0109)	(0.0087)	(0.0116)	(0.0087)
log(*HYE*)	−0.0671***	0.0013	−0.0673***	0.0010
	(0.0146)	(0.0103)	(0.0141)	(0.0104)
log(*SAW*)	−0.0116	−0.0041	−0.0123	−0.0038
	(0.0088)	(0.0055)	(0.0091)	(0.0059)
log(*NCR*)	−0.0725***	−0.0210***	−0.0721***	−0.0210***
	(0.0072)	(0.0046)	(0.0072)	(0.0050)
log(*RNE*)	−0.0269***	−0.0243***	−0.0254***	−0.0241***
	(0.0087)	(0.0053)	(0.0097)	(0.0054)

Note: This table presents the estimation results of the spatial and time-fixed effects SDM and the estimated direct and indirect effects. Spatial lag variables indicate the $W{\cdot}Y$ and $W{\bullet}X$ components in Eq. (6). The standard errors for the estimated coefficients are reported in parentheses. ***, ** and * denote the significance at the levels of 1%, 5% and 10%, respectively.

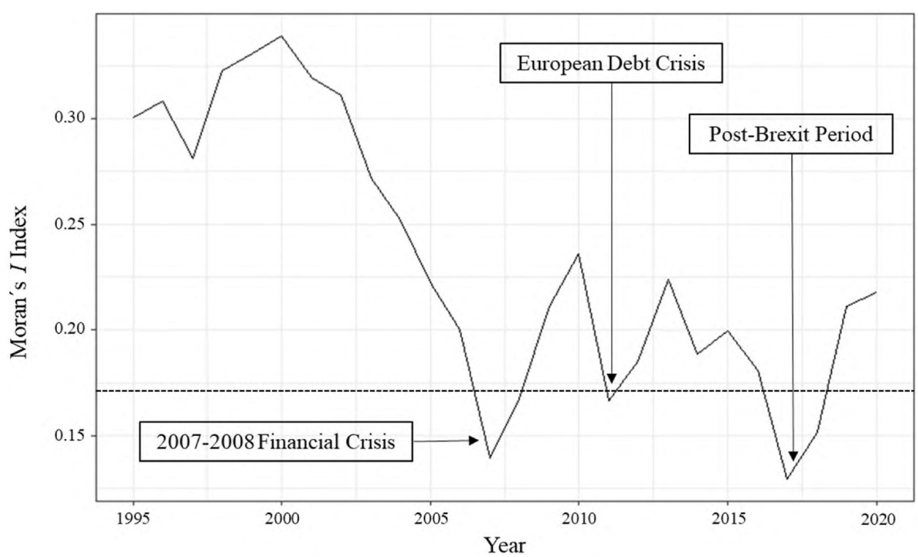

Fig. 7. Plot of Global Moran's *I* Index and Political and Economic Events. Note: The dotted horizontal line in the plot implies the 10% significance level.

to International Energy Agency, in 2021, NG from Russia accounted for around 45% of EU gas imports and close to 40% of its total gas consumption [71]. It implies that if Russia stopped the NG supply completely, there would be, on average, an approximately 10% supply gap in the EU. However, whether the US, Norway, and other gas suppliers can fill this gap timely remains to be questioned. Due to geographic and political constraints, it is difficult for EU countries to further develop hydropower and nuclear power, even though these two energy sources are negatively correlated with CO_2 emissions. Punys et al. (2019) pointed out that hydropower potential is almost exhausted in Europe, especially in those old EU countries [72]. Regarding nuclear power, in many countries, such as Austria, the debate about the possibility of using nuclear power remains muted, while in other countries, such as Belgium and Germany, the nuclear phase-out process is continuing [73,74].

In terms of other RE sources, it is found that wind and solar energy is CO_2-neutral that an increase in its installed capacity is not significantly correlated with CE. A significantly negative relationship is here not observed mainly due to the difference in the stages of adopting this energy source in the studied countries. In contrast, we find evidence that other RE sources negatively affect CE. However, it must be borne in mind that the development of these energy sources is characterized by decentralization in the EU. For instance, the RE is promoted in France and Germany by using the feed-in tariff to attract private investments [12,75]. The expectation of a rapid increase in the installed capacities of these energy sources is, thus, unrealistic. Therefore, it seems that for the EU, the only solution left for the current energy crisis is to raise coal and oil consumption. However, our study indicates that compared to other energy sources, these two fossil fuel types have the strongest positive effects on CE.

In the end, our direct and indirect effects estimation results suggest that many energy sources have both direct and indirect effects. In the first and second KP commitment periods, individual targets have been set for the member states of the EU under the “burden-sharing” framework [4,5]. However, our results indicate that setting individual targets might not be the best measure for the EU in reducing CE since the energy consumption in one country can also affect the CO_2 emissions in its neighboring countries. Thus, countries that put great effort into pushing the energy transition might still fail to reduce their CE when adjacent countries lack the conditions or motivations to do it. Especially as Mata Pérez et al. (2019) mentioned, there are considerable differences in the speed and motivation with which member states pursue the energy transition. This also reflects in the energy structures of the studied countries illustrated in Figs. 2–5 and Fig. S6 in Supplementary Material. Thus, a joint-effort among member countries is needed, and the EU also has favorable conditions to realize this joint-effort. As a supranational political and economic union, the EU can launch policies and legislations and grant funding to facilitate cooperation among the countries. Besides, there are almost no barriers among these member states, so that cross-border transfers of energy technologies, technical personnel, and financial resources can be efficiently accelerated.

5. Conclusion and implications

To the best of our knowledge, our research is the first study that comprehensively investigates the impacts of different energy sources on CO_2 emissions in the EU. Using more recent data, our results can also provide implications for the current energy crisis in the EU. We find that EU countries are in different phases of the energy transition. Besides, it is observed that the CO_2 emissions in the EU show positive and significant spatial dependence, and its strength is affected by global economic and political events. Our SDM estimation provides evidence that in the EU, there is diseconomies of scale effect in CO_2 emissions, and the EKC hypothesis related to economic growth holds. Regarding different types of energy sources, coal and oil are positively correlated with CE, and the relationships are tested to be significant. In contrast, except for solar and wind energy, further consumption of other RECE sources is significantly correlated with decrease in emissions. NG is the only fossil fuel source that is tested to have nonsignificant impact on CO_2 emissions. Thus, due to the lack of NG, restarting coal- and oil-fired power plants to meet the current NG shortage could significantly increase CE in the EU. Furthermore, except for NG and solar and wind energy, the consumption of all the other studied energy sources has either direct effect, indirect effect or both.

Based on our results, some policy implications are provided. The current energy crisis caused by Russia’s war on Ukraine impacts EU energy structure and security in both short- and long-term. The current study shows that NG is compared to other fossil fuels cleaner and compared to RE more reliable. A phase-out of NG is currently not practical both economically and technologically. Therefore, facing the vast supply gap, all countries in EU should diversify their NG supply by finding new suppliers. However, such decoupling from Russia’s NG supply means that infrastructure, such as liquified NG receiving terminals, must be constructed. In addition, a last-minute delay in shutting down nuclear power plants in EU countries, such as Germany, is also an option but only for short-term. In the long-term, EU should accelerate the energy transition to shift from fossil-based energy systems to RECE. In particular, compared to wind and solar energy, bioenergy still has high potential in advancing technology and improving the adoption rate. In addition, the CE reduction in the EU requires inter-regional joint effort, which the EU has favorable conditions to realize.

Ultimately, we provide suggestions for future studies on EU CO_2 emissions. In the current study, it is evident that affluence, proxied by GDP per capita, has a negative effect on CE in the studied countries. This finding is in line with the assumption of the *STIRPAT* model and the EKC hypothesis that after reaching the threshold, further increase in affluence is negatively related to CE. However, the economic disparity between old EU countries, i.e., EU-15, and new EU countries, is still large. In our study, we only analyze the average effect of economic growth on CO_2 emissions for both old and new EU member countries. Thus, it is advisable for future studies to examine to what extent is the current economic growth negatively correlated with CO_2 emissions in old EU countries and what is the impact of affluence on CE in new EU member states.

Credit author statement

Yang Liu: Conceptualization, Methodology, Investigation, Data Curation, Writing-Original Draft, Writing-Review & editing; **Xiaoqing Xie:** Data Curation, Writing-Original Draft, Methodology, Supervision, Writing-Review & editing; **Mei Wang:** Conceptualization, Methodology, Writing-review & editing, 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.energy.2023.128129.

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