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Can Compulsory Ecological Compensation for Land Damaged by Mining Activities Mitigate CO_2 Emissions in China?

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Chinese government has proposed a national contribution plan that involves achieving the peak CO_2 emissions by 2030 and carbon neutrality by 2060. To explore the pathway of achieving carbon neutrality, we tried to use resources taxes and land reclamation deposits as compulsory ecological compensation (CEC). In order to test if CEC can affect CO_2 emissions, energy intensity was selected as the intermediate variable. We found that the CO_2 emissions trend in China is consistent with environmental Kuznets curve hypothesis and proved that CEC displayed a spillover effect on energy intensity. Likely, energy intensity presented a spillover effect on CO_2 emissions. Therefore, CEC will spatially affect CO_2 emissions. The generalized spatial two-stage least-squares estimate model was used to identify the impact mechanism of coal production on energy intensity with CEC as the instrumental variable. The results indicated that reducing coal production in neighboring regions may cause the mitigation of local CO_2 emissions. Finally, regression analyses carried out by region suggested regional cooperation should be carried out in the process of carbon mitigation.

Keywords: CO_2 emissions, compulsory ecological compensation, environmental Kuznets curve, intermediate variable, spatial econometric model

INTRODUCTION

The Chinese government has proposed a national contribution plan achieving the peak CO_2 emissions by 2030 (Malakoff, 2014) and carbon neutrality by 2060 (Cui et al., 2021). However, China contributed the most CO_2 emissions in the world. Because the energy intensity (energy consumption per unit of GDP) is much higher in China than that for other countries (Li et al., 2015). Wang et al. (2019) attributed excessive energy consumption to the fact that energy prices did not include environmental costs. Energy price is the essential factor for carbon intensity and energy intensity and is the crux to CO_2 emission mitigation (Lin and Liu, 2010). However, coal contributed 82.9% of CO_2 emissions (Lin and Wu, 2018). Therefore, coal should be charged for its external costs to reduce energy intensity and CO_2 emissions in China. Besides, coal mining is the main reason for the damaged land (He and Su, 2002). The damaged area caused by mining reached 47,661 hectares in 2017 (MLR, 2018). To test whether compensation for the damaged land caused by mining not only can reduce energy intensity but also can mitigate CO_2 emissions is the original intention of this study.

According to the principle of who destroys who governs, the Chinese government imposed compensation fees including resource taxes according to the exploited resources and the security deposit paid for the remediation and restoration of the mine geological environment according to damaged areas caused by mining. For specific terms, refer to Article 5 of the Implementation Rules of the Mineral Resources Law of the People's Republic of China[1] and Article 18 of the Regulations on Mine Geological Environment Protection[2]. According to these, we set up an indicator called compulsory ecological compensation (CEC). Existing ecological compensation policies focus only on how to subsidize land reclamation, and resource taxes are not used to mitigate CO_2 emissions. As China is setting more light on the development quality, economic development can no longer rely on energy consumption regardless of external costs. Economic development can no longer rely on energy consumption regardless of external costs. CEC can be considered as compensation for the negative externalities caused by coal mining. However, regarding ecology compensation, previous studies either only focus on the land loss of stakeholders (Kidido et al., 2015; Adonteng-Kissi, 2017; Shackleton, 2020) or highlight its impact on sustainable development (Novoselov et al., 2021). Although the interconnecting mechanism between land loss and coal-fired pollution emissions has been recovered (Li et al., 2019b), previous research has not fully considered the relationship between ecological compensation and CO_2 emission mitigation.

To fill these gaps, this study tried to reveal the mechanism that CEC for damaged land has a spillover effect on CO_2 emissions by spatially affecting energy intensity. First, we used spatial econometrics to estimate CO_2 emissions and energy intensity in two stages. Second, we focus on the study of the impact of coal production on energy intensity in different regions. Our article is organized as follows. The second part is the literature review and the induced hypothesis. The methodology is shown in the third section. The following section is the results and discussion. In the end, we present the conclusion.

LITERATURE REVIEW

The Relationship Between Charging for Environmental Externalities and CO_2 Emissions

Studies have also come to different conclusions about the effects of compensation on the environment. For example, Silva et al. (2021) argued that financial compensation for mining activities is useless for mitigating the negative environmental impacts in Brazil. By contrast, Bennett et al. (2018) proved that environmental compensation indeed mitigates negative externality. The reason for this difference is that the objects of compensation are different. Mining activities in other countries mainly refer to nonenergy minerals, whereas coal mining is the dominant mining activity in China. Charging for coal resources would be more inclined to mitigate CO_2 emissions.

Compensation, carbon taxes, and resource taxes can be used as policy instruments to charge for environmental externalities. For example, Whitmore (2020) concluded that compensation could be a motivation tool to manage climate change. In addition, previous studies suggested carbon taxes are helpful to reduce energy demand (Lin and Jia, 2018; Liu et al., 2018) and mitigate CO_2 emissions (Li et al., 2019a; Wang and Yu, 2021). Moreover, the effect of mineral rent on CO_2 emissions has been revealed (Yue et al., 2020). Resource tax is beneficial to achieve efficient utilization of coal by increasing the cost. Shen et al. (2021) found that resource taxes could mitigate CO_2 emissions. Lin and Jia (2020) insisted that resource taxes can manage negative environmental externalities such as carbon emissions more effectively by controlling supply. Wang and Yu (2021) argued that the resource tax should not be too low because it can effectively control carbon emissions. These all show that charging for the negative environmental externalities is of great significance for CO_2 emission mitigation in China.

Coal Production and Energy Intensity

Coal production and energy intensity are interrelated. The relationship is not as apparent as it is with carbon emissions. A good example is in coal-rich East Europe; the reliance on coal has led to relatively higher energy intensity (Nielsen et al., 2018). Likewise, it has been proved that some Western European countries such as Britain and Germany have been slow to decline in energy intensity because they have access to cheap coal (Fouquet, 2016). The type of energy consumed is proved to be the determining factor in declining energy intensity (Gentvilaite et al., 2015). As coal is a relatively cheap energy source, too much reliance on it will not help improve energy intensity. Some Nordic countries that lack coal endowments, such as Sweden, declined their energy intensity decline rapidly (Kander et al., 2017).

Spatial Correlation of Energy Intensity and CO_2 Emissions

Previous research has proved the unbalanced development of regional energy intensity exists (Song et al., 2018; Yu et al., 2018; Wang et al., 2019; Mussini, 2020). And it is concluded that energy intensity was one of the dominating factors determining the spatiotemporal patterns of China's carbon intensity (Cheng et al., 2014) and revealed energy intensity displays a spillover effect in China (Wang et al., 2019). Besides, neighborhood effects of CO_2 emissions have been recovered (Mussini, 2020; Shahnazi and Shabani, 2021). It enlightened us that the spatial analysis of energy intensity and CO_2 emissions should be adopted.

Literature Revelation and Hypothesis

Combing the literature, we get the following three points: (1) charging for environmental externalities can mitigate carbon emissions; (2) coal production is closely related to energy

[1]http://f.mnr.gov.cn/201907/t20190728_2449555.html
[2]http://f.mnr.gov.cn/201702/t20170206_1436681.html

intensity; and (3) both energy intensity and carbon emissions have spatial autocorrelation. However, how charging for environmental externalities affects CO_2 emissions is not clear. Considering coal production could affect the trajectory of energy intensity, and energy intensity and carbon emissions are closely linked, we put forward the hypothesis that coal production will affect CO_2 emissions positively by influencing energy intensity. We expect to prove that charging for coal production could act as an instrument in mitigating the CO_2 emission process. We aim to reveal the spatial spillover effect of charges on CO_2 emission mitigation. Our innovation is to consider CEC for damaged land as an incentive instrument.

DATA AND METHODOLOGY

The Definition of CEC

We set up an indicator named CEC. It is the sum of the resources tax and the security deposit paid for the remediation and restoration of the mine geological environment. The data of resource tax are taken from the China Tax Yearbook,[3] and the data of mine geological environment restoration deposit is taken from the China Land and Resources Statistical Yearbook.[4] Although it may be lower than the cost of ecology restoration, it is still the most reliable data.

Data Processing

The Calculation of CO_2 Emissions and Energy Intensity

In order to verify the spatial aggregation effect and heterogeneity of CO_2 emissions and clarify the effect factors, we first calculated CO_2 emissions and the energy intensity. CO_2 emissions mainly stem from the consumption of fossil energy and industrial processes. This calculation does not include CO_2 emissions of the agricultural process because the CO_2 emissions calculated in the first two parts have accounted for more than 90% of the whole, and CO_2 emissions from agriculture energy consumption have been included when calculating fossil energy. Moreover, the impact of CEC on the energy intensity of the agriculture process is not as significant as that of fossil energy consumption and industrial processes.

(1) CO_2 emissions from the consumption of fossil energy. Previous studies (Cheng et al., 2014; Wu et al., 2020; Zhang et al., 2020) used eight kinds of fossil energy sources to build the formula (**Equation 1**).

$$Emc_{i,t} = \left(1.012 \times \sum_{j=1}^{8} E_{i,j} \times LCV_j \times CEF_j \times COF_j + Cem_i \times EF_{cem}\right) \times \frac{44}{12} \tag{1}$$

Herein, $Emc_{i,t}$ corresponds to the total CO_2 emissions in province i for year t; $E_{i,j}$ indicates the natural gas, diesel oil, coal oil, gasoline, fuel oil, crude oil, coke, and coal, which corresponds to the eight types of fossil energy used for year t in province i; LCV_j represents the average low-order calorific value for each type of fossil energy that can be found in Appendix 4 of the China Energy Statistical Yearbook (NBS, 2018); CEF_j denotes the carbon content of energy j; COF_j is the rate of carbon oxidation. The values of CEF_j and COF_j were taken from IPCC (2006).

(2) CO_2 emissions from the industrial process. The coefficient 1.012 represents the total emissions resulting from fossil energy consumption and other industrial processes such as ammonia production, lime production, and steel production. These are equivalent to 1.2% of China's emissions from fossil fuel combustion (Liu et al., 2015). Besides, CO_2 emissions from cement production were introduced. Cem_i denotes cement production in province i; EF_{cem} represents the cement emission factor, which displays a value of 0.1065 (IPCC, 2006; Liu et al., 2015); and 44/12 is the molecular weight ratio of CO_2.

Energy intensity is expressed as the ratio of energy consumption to GDP (Cheng et al., 2014; Li et al., 2019b; Liu and Song, 2020). In order to calculate energy intensity, in addition to fossil fuels, we added electricity.[5] Each energy source was converted into its corresponding standard coal consumption and is shown in **Eq. 2**.

$$Ein_{i,t} = \frac{1}{GDP} \sum_{j=1}^{8} \left(E_{i,j} \times LCV_j + Ele_i \times LCV_e\right) \tag{2}$$

$Ein_{i,t}$ represents energy intensity in province i for year t; Ele_e corresponds to electricity consumption in province i for year t; LCV_e indicates the average low-order calorific value of electricity; the values were taken from **Supplementary Appendix S4** of the China Energy Statistical Yearbook, 2018.

The Method to Test Spatial Correlation

To test the spatial relationship among CEC, CO_2 emissions, and energy intensity, Moran's I[6] was used. Both Moran's I and spatial analysis need to determine spatial weight matrix initially. The weight matrix represents the importance of each province. According to Tobler's first law of geography, the attributes of spatial observations close to each other are more similar than those dispersed. We also used a row-normalized inverse distance weight matrix $W_{i,j}$, which equals $1/d_{i,j}$. $d_{i,j}$ represented the distance between the i and the j $(i \neq j)$ provinces, based on the latitude and longitude of the capital city in each province. This spatial weight matrix

[3]https://data.cnki.net/yearbook/Single/N2020050205

[4]https://data.cnki.net/yearbook/Single/N2020030130

[5]In order to avoid double calculations, the electricity consumption refers to electricity consumption from non-fossil energy sources.

[6]Moran'I statistic: $= \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}(x_i-\bar{x})(x_j-\bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}}$, among them $S^2 = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n}$ is the sample variance, $w_{i,j}$ is the spatial weight matrix. $\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}$ is the sum of all weights. The value of Moran'I ranges from -1 to 1, and greater than 0 indicates a positive correlation. In other words, the high values are adjacent to the high ones, and the low values are adjacent to the lows. A value less than 0 indicates a negative correlation, which denotes the high values are adjacent to the low values.

TABLE 1 | List of explanatory variables used in the analysis and data sources.

Name of variable	Description	Data source
E	Eight types of fossil energy (10^4 tons) including natural gas, diesel oil, coal oil, gasoline, fuel oil, crude oil, coke, and coal	China energy statistical yearbook
Cem	Production of cement (10^4 tons)	National Bureau of Statistics: https://data.stats.gov.cn
Emc	CO_2 emissions (10^4 tons)	Calculated using **Eq. 1**
GDP	Gross domestic production (10^4 CNY)	National Bureau of Statistics: https://data.stats.gov.cn
Pop	Population (10^4 persons)	National Bureau of Statistics: https://data.stats.gov.cn
Ein	Energy intensity (t/10^4 CNY)	The ratio of the total energy consumption (standard coal equivalent) to GDP
FDI	The ratio of foreign direct investment to total GDP	National Bureau of Statistics: https://data.stats.gov.cn
Urba	Urbanization: the proportion of urban population in the total[a]	National Bureau of Statistics: https://data.stats.gov.cn
Ist	Industrial structure: the percentage of industrial added value to GDP[b]	National Bureau of Statistics: https://data.stats.gov.cn
Epr	Coal prices (Qinhuangdao port, 5,500 kcal/kg)	Wind Database
Cpro	Coal production	China energy statistical yearbook
CEC	Compulsory ecological compensation (resources tax plus amount of security deposit)	Security deposit: China land and resources statistical yearbook; resources tax: China Tax Yearbook

Notes: [a]This kind of expression is questioned due to the inconsistency of the household registration system with population movements (Ni et al., 2014) and the reasonableness of statistical calibers (Tao and Xu, 2005), and so on, to simplify the analysis, we used this indicator to represent the level of urbanization. [b]This variable was used by Lin and Jiang, (2009).

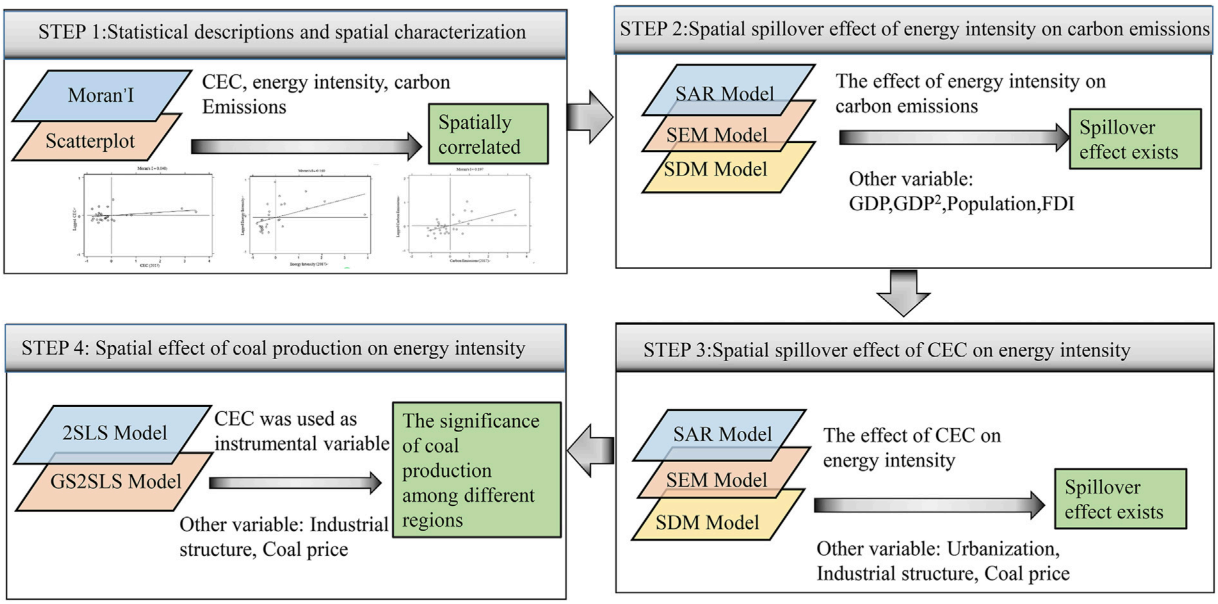

FIGURE 1 | Research framework diagram.

ensures that variables of neighboring provinces decrease with distance and vice versa. **Table 1** shows the description and sources of each variable.

Research Framework

As coal resources display regional disparity among provinces, the damaged land caused by coal mining activities has the characteristics of spatial aggregation. CEC for the damaged land (**Supplementary Figure S1**) is also spatially converged and heterogeneous. It has been concluded that CO_2 emissions are also spatially heterogeneous (Liu and Liu, 2019; Li et al., 2020; Li and Li, 2020).

To investigate the impact mechanism of CEC for destructed land on CO_2 emissions and to avoid bias, spatial spillover effects analysis was used in this study. Furthermore, we used energy intensity as an intermediate variable. To research the mechanism of CEC on CO_2 emissions, the research framework contained four steps (**Figure1**).

Step 1: We tested spatial convergence spatial correlation characteristics using Moran's *I* and Moran scatterplot.

Step 2: The spillover effect of energy intensity on CO_2 emissions was examined by comparing three spatial econometric models of the spatial Durbin model (SDM), the spatial lag model (spatial autoregressive [SAR]), and the spatial error model (SEM).

Step 3: SAR, SEM, and SDM models were compared to test the spillover effect of CEC on energy intensity.

Step 4: Using generalized spatial two-stage least-squares estimates (GS2SLSs) to analyze the impact of CEC and coal production on energy intensity. As CEC would increase the cost of coal mining and affect coal production, coal production was considered as an explanatory variable of energy intensity.

The Model Specification

Considering the particularity of the geographical environment of Tibet and the poor availability of data for Hong Kong, Macao, and Taiwan, we selected annual panel data for 30 provinces covering the period 2009–2017.

Spatial econometrics method was selected to test the direct and the spillover effect of damaged land compensation on energy intensity and CO_2 emissions. According to the strategy proposed by Belotti et al. (2016) and Elhorst (2014), we selected panel SDM as a general specification and tested for the alternatives. The panel SDM is represented in **Eq. 3**:

$$Y_{i,t} = \rho \sum_{j=1}^{n} W_{i,j} Y_{i,t} + \beta X_{i,t} + \sum_{j=1}^{n} W_{i,j} X_{i,t} \theta + \mu_i + \mu_t + \varepsilon_{i,t} \quad \varepsilon_{i,t} \sim i.i.d\left(0, \sigma^2\right) \tag{3}$$

where $Y_{i,t}$ is a vector of the dependent variable for province i and year t; $(i = 1, \ldots, n, t = 1, \ldots, T)$. $\sum_{j=1}^{n} W_{i,j} Y_{i,t}$ represents the effects of the interaction between the dependent variables of neighboring provinces. ρ is the spatial autoregressive coefficient that measures the magnitude of interaction among provinces. $X_{i,t}$ is a matrix of observations for the explanatory variables with an associated vector of coefficients β. θ indicates the spatial lag coefficients of explanatory variables, whereas μ_i and μ_t are the fixed effects of space and time, respectively. $\varepsilon_{i,t}$ represents the error term, which is independent and identically distributed with the mean equals zero; the variance is σ^2. $W_{i,j}$ corresponds to the weight matrix. Following Elhorst (2014), from the panel SDM, a family of spatial econometric models can be deduced using the likelihood ratio tests. If the restriction $\theta = -\rho\beta$ is considered, the SEM can be obtained. It indicates that spatial dependence exists only in the error term. If $\theta = 0$ and $\rho \neq 0$, the SAR model is obtained. This model implies that spatial dependence only occurs for the dependent variable and reveals the interrelation of dependent variables among adjacent provinces.

CO_2 emissions are the dependent variables in the first stage. **Eq. 4** presents the initial dependent variable ($Emc_{i,t}$); the descriptions of other explanatory variables are shown in **Table 1**. The environmental Kuznets curve (EKC) hypothesis was examined by Grossman and Krueger (1995) and Shafik and Bandyopadhyay (1992), and it has been proven at the city level, province level, and national level in China (Kang et al., 2016; Jiang et al., 2019; Chen et al., 2020). We determined selecting the squared term of GDP for that the relationship between economic development level and CO_2 emissions should not be linear.

$$\begin{aligned} lnEmc_{i,t} = {} & \alpha_i + \rho \sum_{j=1}^{n} W_{ij} lnEmc_{i,t} + \beta_1 lnGDP_{i,t} + \beta_2 \left(lnGDP\right)^2_{i,t} \\ & + \beta_3 lnPop_{i,t} + \beta_4 Ein_{i,t} + \beta_5 FDI_{i,t} \\ & + \varphi_1 \sum_{j=1}^{n} W_{i,j} lnGDP_{i,t} + \varphi_2 \sum_{j=1}^{n} W_{i,j} \left(lnGDP\right)^2_{i,t} \\ & + \varphi_3 \sum_{j=1}^{n} W_{i,j} lnPop_{i,t} + \varphi_4 \sum_{j=1}^{n} W_{i,j} Ein_{i,t} \\ & + \varphi_4 \sum_{j=1}^{n} W_{i,j} Ein_{i,t} + \varphi_5 \sum_{j=1}^{n} W_{i,j} FDI_{i,t} + \mu_i + \mu_t + \varepsilon_{i,t} \end{aligned} \tag{4}$$

The references related to independent variables are shown in **Table 2**. According to previous studies (Liu and Liu, 2019; Li et al., 2020; Li and Li, 2020; Liu and Song, 2020; Zhang et al., 2020), we chose the energy intensity as the explanatory variable in the initial. The multicollinearity problem of selected variables was tested by variance inflation factor (VIF) test (**Tables 3**, **4**).

We started by hypothesizing that energy intensity (*Ein*) is an endogenous variable. Then, the Hausman specification test was used to test the endogeneity of *Ein*. When the null hypothesis is not rejected, we can affirm the SDM model provides a consistent estimation and ensures a relatively small variance. In order to recover the impact mechanism of CEC on energy intensity, we introduced **Eq. 5** and chose $Ein_{i,t}$, *Urba*, *Ist*, *lnCEC*, and *lnEpr* as explanatory variables. The descriptions of the variables are summarized in **Table 1**. The references are in **Table 2**. We start the analysis with the panel SDM.

$$\begin{aligned} Ein_{i,t} = {} & \alpha_i + \rho \sum_{j=1}^{n} W_{ij} Ein_{i,t} + \beta_6 Urba_{i,t} + \beta_7 Ist_{i,t} + \beta_8 lnCEC_{i,t} \\ & + \beta_9 lnEpr_{i,t} + \varphi_6 \sum_{j=1}^{n} W_{i,j} Urba_{i,t} + \varphi_7 \sum_{j=1}^{n} W_{i,j} Ist_{i,t} \\ & + \varphi_8 \sum_{j=1}^{n} W_{i,j} lnEC_{i,t} + \varphi_9 \sum_{j=1}^{n} W_{i,j} lnEpr_{i,t} + u_i + u_t + \varepsilon_{i,t} \end{aligned} \tag{5}$$

As most of the damaged land has been caused by coal mining activities, $Cpro$ was used as a new explanatory variable and *Ist* and *lnEpr* as the remaining explanatory variables. GS2SLS methods were applied (Kelejian and Robinson, 1993; Kelejian and Prucha, 1999) if coal production was endogenous. Finally, because of the spatial heterogeneity of coal distribution, China's territory was divided into three regions: the east, central, and west (**Supplementary Figure S3**). The GS2SLS method was applied in order to perform a regional analysis and provide a basis for interaction between regions during CO_2 emission mitigation.

RESULTS AND DISCUSSION

Multicollinearity Tests

Tables 3 and **4** show that the selected variables for **Eqs 4**, **5** are correlated to a low degree. The values of the coefficients are all less

TABLE 2 | Summary of factors determining dependent variables.

Dependent variable	Explanatory variable	Findings in the previous research
Carbon emissions	Per capita GDP or GDP	Yang et al. (2019); Zhang et al. (2020); Wu et al. (2020); Li and Li (2020); Li et al. (2020); Liu and Liu (2019); Liu and Song (2020); Cui et al. (2019); Chen and Lee (2020)
	The squared term of GDP	Wu et al. (2020); Li and Li (2020)
	Population	Yang et al. (2019); Li et al. (2020); Liu and Liu (2019); Chen and Lee (2020)
	Energy intensity or energy efficiency	Zhang et al. (2020); Li and Li (2020); Li et al. (2020); Liu and Liu (2019); Liu and Song (2020)
	FDI	Cheng et al. (2014); Long et al. (2020)
Energy intensity or carbon intensity	Industrial structure	Wang et al. (2019); Song et al. (2018); Lv et al. (2017); Long et al. (2016); Cheng et al. (2014)
	Energy price	Wang et al. (2019); Lv et al. (2017); Zhong et al. (2018); Neng (2011)
	CEC of destructed land	Our new idea

TABLE 3 | Correlation coefficient matrix and VIF tests for *lnEmc*.

Dependent variable: *lnEmc*	VIF	*lnEMC*	*lnGDP*	*lnPop*	*Ein*	*FDI*
lnEMC		1.000				
lnGDP	4.36	0.466***	1.000			
lnPop	3.81	0.522***	0.697***	1.000		
Ein	1.46	0.041***	0.251***	0.127***	1.000	
FDI	1.31	0.010	0.054***	0.000	0.129***	1.000

Notes: ***$p < 0.1$.

TABLE 4 | Correlation coefficient matrix and VIF tests for *Ein*.

Dependent variable: *Ein*	VIF	*Ein*	*Urba*	*Ist*	*lnCEC*	*lnEpr*
Ein		1.000				
Urba	1.34	0.111***	1.000			
Ist	1.27	0.009	0.038***	1.000		
lnCEC	1.51	0.049***	0.195***	0.120***	1.000	
lnEpr	1.21	0.007	0.019**	0.082***	0.120**	1.000

Notes: **$p < 0.05$, ***$p < 0.1$.

than 0.8. The VIF values are all less than 10. We could conclude that multicollinearity does not exist in explanatory variables in the equations.

Statistical Descriptions and Spatial Characterization of CEC, CO_2 Emissions, and Energy Intensity

Supplementary Figures S2A,B show the spatial distribution of CO_2 emissions in each province. Data indicated that CO_2 emissions in China display spatial agglomeration. High-carbon emission areas are those rich in coal resources, such as Shanxi, Inner Mongolia, and Xinjiang and the developed provinces such as Shandong, Jiangsu, and Guangdong. **Supplementary Figures S2C,D** show that energy intensity is also spatially agglomerated. The high-value provinces are leading coal producers, such as Inner Mongolia, Shanxi, Xinjiang, and Ningxia.

Table 5 shows the results of Moran's *I* for CEC, CO_2 emissions, and energy intensity. The values are all positively significant at the 5% level, indicating that CEC, *Emc*, and *Ein* are spatially converged.

The scatterplot points mostly fall in the first (the upper-right region formed by the *x*-coordinate and the *y*-coordinate) and third quadrants (the lower-left region formed by the *x*-coordinate and the *y*-coordinate) (**Figure 2**). When the scatter falls in the first quadrant, it means that the high value is adjacent to the high value, and when the scatter falls in the third quadrant, it means that the low value is adjacent to the low one. CEC is closely related to the land damaged by coal mining. However, the distribution of coal resources in China has significant regional differences and shows the characteristics of relatively concentrated aggregation. Specifically, it is mainly distributed in the north, the northeast, northwest, and southwest. That is the reason why CEC (**Figures 2A,B**) presents spatial aggregation. These results indicated that energy intensity (**Figures 2C,D**) and CO_2 emissions (**Figures 2E,F**) are highly spatial correlated. In other words, it shows high–high agglomeration and low–low agglomeration.

TABLE 5 | Moran's I statistics of CEC, CO_2 emissions and energy intensity from 2009 to 2017.

Moran's I	CEC	*Emc*	*Ein*
2009	0.039**	0.163**	0.155**
	[0.036]	[0.093]	[0.088]
2010	0.167**	0.191***	0.163**
	[0.094]	[0.094]	[0.087]
2011	0.028	0.181**	0.170**
	[0.085]	[0.095]	[0.085]
2012	0.044	0.218***	0.197**
	[0.093]	[0.095]	[0.089]
2013	0.019*	0.229***	0.146***
	[0.034]	[0.090]	[0.077]
2014	0.134*	0.237***	0.143***
	[0.095]	[0.089]	[0.076]
2015	0.014*	0.237***	0.144***
	[0.034]	[0.090]	[0.076]
2016	0.024**	0.212***	0.144***
	[0.034]	[0.091]	[0.077]
2017	0.040***	0.197***	0.169***
	[0.032]	[0.089]	[0.083]

*Notes: The values in brackets correspond to standard errors, *p < 0.01, **p < 0.05, ***p < 0.1.*

Spatial Spillover Effects of Energy Intensity on CO_2 Emissions

According to **Table 2**, when we estimate the equation with carbon emissions as the dependent variable, GDP, the squared term of GDP, population, and *FDI* could be chosen as the explanatory variables. When energy intensity was selected as the dependent variable, *FDI*, industrial structure, energy price, and CEC could be used as independent variables. Thus, we tried to establish a carbon emission determination model using the above explanatory variables with the help of the GS2SLS method. In the equation, *Ein* was chosen as the endogenous explanatory variable. Hausman specification test (Hausman, 1978) results (Hausman value equals −0.621, and the p value equals 0.987) show that the *Ein* is not endogenous. Given this result, we used the xsmle estimator[7] in Stata, according to Belotti et al. (2016), and obtained the spatial panel estimation models. *Ein* was used as an explanatory variable analyzing CO_2 emissions (**Table 2**). The results (**Table 6**) indicate that the SDM model shows the best specification of all three models. **Table 6** shows the results for spatial spillover effects of energy intensity on CO_2 emissions. The Hausman tests indicated that fixed effects are suitable for all the models. Thus, the SDM model was chosen in the initial. In addition, the spatial ρ is significant, which denotes that spatial correlation ship exists among provinces (**Table 6**). Moreover, results indicate that GDP is positive, and the coefficient of GDP squared is negative. These data support the validity of the EKC hypothesis for Chinese provinces. In addition, the coefficients of *Pop*, *FDI*, and the corresponding lagged terms are all insignificant. *Ein* and its spatially lagged term are all statistically significant. Their coefficients are equal to 0.533 and 0.643, respectively. Besides, the indirect effect of *Ein* is significant (**Table 7**).

Carbon constraints have not been implemented in China, which is probably why *Ein* is not endogenous. In addition, the bidirectional transmission channel between CO_2 emissions and energy intensity has not been established. However, it can be predicted that if a carbon-restraint mechanism is established in the future, *Ein* will become an endogenous variable for CO_2 emissions. The significant coefficients of GDP and its squared term imply that China's carbon peak target is achievable. Data for CO_2 emissions show an inverted U-shaped curve. As GDP grows, CO_2 emissions will inevitably present an inflexion point. This conclusion can be supported by Baz et al. (2020) and Yue et al. (2020). The lagged term of the *FDI* is not significant, which indicates that *FDI* does not significantly influence China's CO_2 emissions. On the other hand, our results differ from those that *FDI* can reduce carbon productivity by bringing technological innovation (Long et al., 2020). And our results are against the previous conclusion that *FDI* has a positive impact on CO_2 emissions (Shahbaz et al., 2018). Thus, China cannot expect to use *FDI* to reduce the energy intensity but should seek other motivation. However, the variable *Ein* and its spatially lagged term indicated that if energy intensity can be reduced by 1%, CO_2 emissions can also be reduced by approximately 0.53%, CO_2 emissions in neighboring provinces can be reduced by approximately 0.65%. The indirect effect of *Ein* proves that the spatial spillover effect of *Ein* is significant. Furthermore, the total effect of *Ein* is significant and higher than its direct effect. It may indicate that energy intensity affects CO_2 emissions not only of the local region but also other regions. Thus, in the process of CO_2 emission mitigation, attention should be paid to the spillover effect of energy intensity. The spillover effects are attributed to industrial transfer among regions (Li et al., 2018) and the mimicry of the neighborhood (Wang et al., 2019). This study insists that the unbalanced distribution and consumption of coal resources lead to the spatial spillover effect of energy intensity on CO_2 emissions. A decrease in energy intensity of neighboring provinces will cause coal exporting decline from coal production provinces.

Spatial Spillover Effects of CEC on Energy Intensity

Although compelling evidence for spatial convergence and correlation of energy intensity in China has been recovered (Liu et al., 2017; Lv et al., 2017; Yu et al., 2018; Wang et al., 2019), we should find out how to reduce Chinese energy intensity. **Table 8** shows spatial spillover effects of CEC on energy intensity, which presents the results of SDM, SAR, and SEM models in the second stage. The spatial error parameter, ρ, was statistically significant in these three spatial panel data models, indicating that energy intensity displays spatial correlation. The SDM model was chosen as it showed the best specification of all three models (**Table 8**). **Table 8** also indicates that the Urba was significantly negative at the 1% level. The indirect effect of CEC negatively impacts energy intensity, with the coefficient value significantly equaling −0.121 (**Table 7**).

[7]It is a computer command for spatial econometrics.

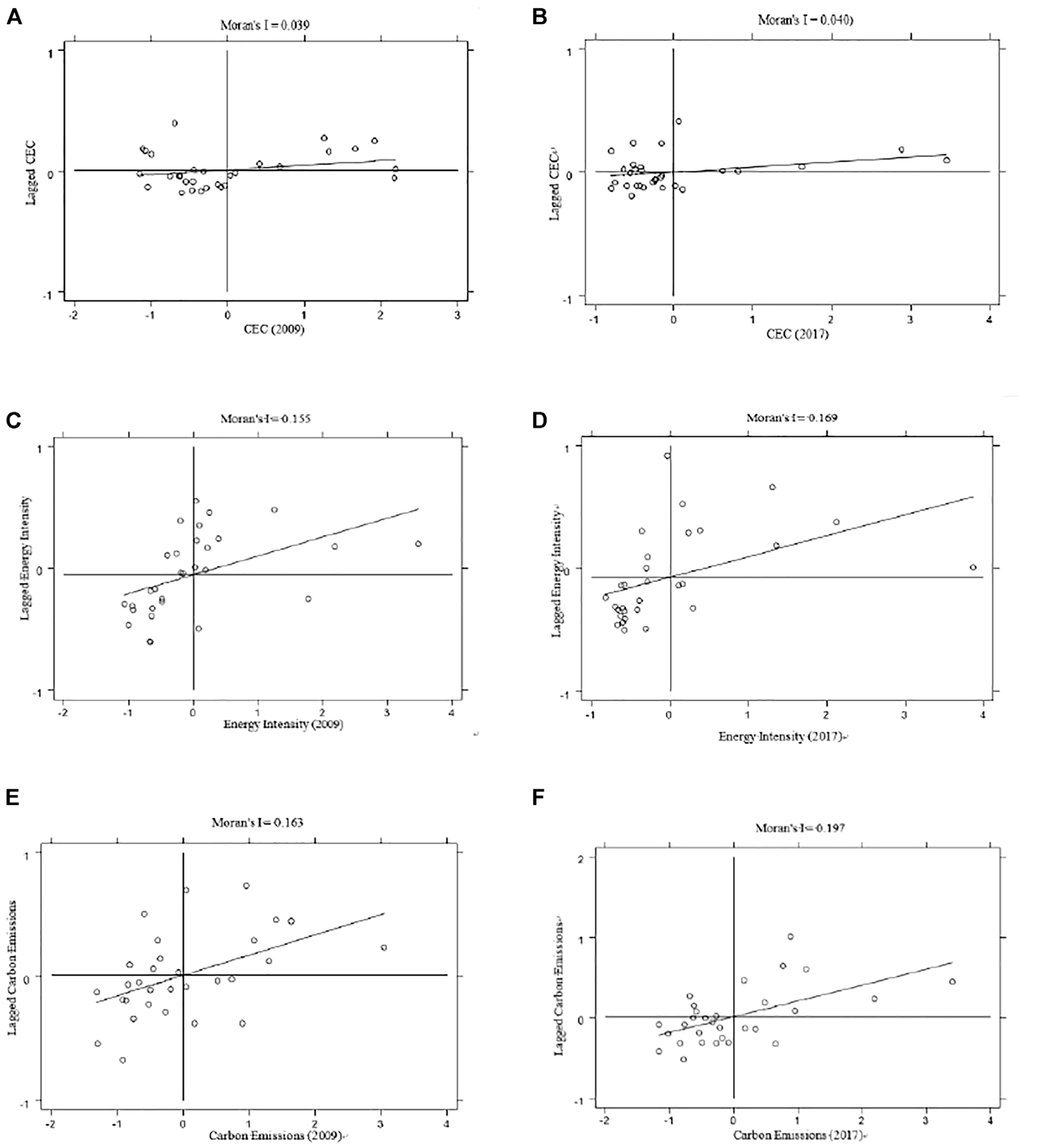

FIGURE 2 | Scatterplots of Moran 'I of CEC, Energy intensiy and Carbon emissions for 2009 and 2017.

The *Urba* variable indicated that the direct impact of urbanization on energy intensity is negative. Urbanization-brought related industries developed. As a result, infrastructures were improved, and energy intensity was reduced (Chen et al., 2019). The spatial lagged *lnCEC* coefficient implies that CEC presented a spillover effect on energy intensity. Therefore, CEC should no longer be an issue of one single region; it should be spatially related. Thus, CEC should be performed at a national level. Combined with the conclusions of *The Definition of CEC* (as the indirect effects are shown in **Table 7**, the spatial spillover effect of CEC on CO_2 emissions can be proven). It reflects a transmission mechanism: CEC has a spatial spillover effect on energy intensity. Meanwhile, energy intensity also has a spatial spillover effect on CO_2 emissions. In other words, for every 1% increase in CEC in the neighboring regions, local CO_2 emissions may be mitigated by

TABLE 6 | Spatial model estimation results in the initial.

	SDM	SAR	SEM
lnGDP	3.974***	4.504***	4.574***
	[1.155]	[0.942]	[0.949]
$(lnGDP)^2$	−0.086***	−0.104***	−0.106***
	[0.033]	[0.026]	[0.025]
lnPop	−0.568	−0.815	−0.843*
	[0.455]	[0.104]	[0.500]
Ein	0.533***	0.503***	0.505***
	[0.094]	[0.089]	[0.092]
FDI	0.589	0.099	0.190
	[6.778]	[1.051]	[1.060]
W·lnGDP	5.603		
	[4.187]		
$W\cdot(lnGDP)^2$	−0.139		
	[0.115]		
W·lnPop	−1.649		
	[3.474]		
W·Ein	0.643***		
	[0.247]		
W·FDI	11.054		
	[6.777]		
Spatial ρ	−0.333**	−0.024	
	[0.167]	[0.140]	
Lambda			−0.169
			[0.210]
Hausman	41.16***	15.12***	15.97**
Model selection test statistics		SAR vs SDM	SEM vs SDM
χ^2		13.99	13.64
p value		0.016	0.018

*Notes: Standard errors in brackets **p < 0.01, **p < 0.05, ***p < 0.1.*

TABLE 8 | Spatial model estimation results of energy intensity.

	SDM	SAR	SEM
Urba	−2.949**	−4.947***	−4.262***
	[1.192]	[1.503]	[0.987]
lnCEC	0.001	0.810	−0.008
	[0.041]	[0.045]	[0.050]
Ist	−2.100	−1.401	−1.175
	[1.732]	[1.241]	[0.998]
lnEpr	0.941	0.083	0.028
	[0.809]	[0.060]	[0.041]
W·Urba	−0.015		
	[2.976]		
W·lnCEC	−0.264***		
	[0.096]		
W·Ist	3.949		
	[2.487]		
W·lnEpr	−1.302		
	[1.129]		
Spatial ρ	−0.905**	−0.352	
	[0.368]	[0. 401]	
Lambda			−0.766***
			[0.274]
Hausman	28.64***	3.48	3.99
Model selection test statistics		SAR vs SDM	SEM vs SDM
χ^2		15.97	16.75
p value		0.001	0.002

*Notes: Standard errors are shown in brackets *p < 0.01, **p < 0.05, ***p < 0.1.*

TABLE 7 | Direct, indirect, and total effects of the SDM models.

Dependent variable: *lnEmc*				Dependent variable: *Ein*			
Variable	Direct effects	Indirect effects	Total effects	Variable	Direct effects	Indirect effects	Total effects
lnGDP	3.933***	2.560	6.493***	*Urba*	−3.008**	1.213	−1.795*
	[1.183]	[2.484]	[1.964]		[1.251]	[1.611]	[0.983]
$(LnGDP)^2$	−0.085**	−0.066	−0.151***	*lnCEC*	0.007	−0.121***	−0.114**
	[0.034]	[0.069]	[0.054]		[0.042]	[0.047]	[0.055]
lnPop	−0.554	−0.874	−1.428	*Ist*	−2.229	2.672	0.443
	[0.467]	[2.081]	[1.951]		[1.857]	[1.750]	[0.656]
Ein	0.528***	0.279*	0.807***	*lnEpr*	0.988	−0.984	0.004
	[0.092]	[0.142]	[0.177]		[0.868]	[0.862]	[0.053]
FDI	0.486	6.496	6.982				
	[1.097]	[4.015]	[4.448]				

*Notes: Standard errors in brackets *p < 0.01, **p < 0.05, ***p < 0.1.*

approximately 0.03%. Previous research insisted people use resources tax (Lin and Jia, 2020; Wang and Yu, 2021) to manage negative environmental externalities and mitigate CO_2 emissions. Others suggested that the coal resources tax is helpful to solve the issue of land damage and CO_2 emissions (Li et al., 2019a). However, this study proved that CEC is helpful for mitigating CO_2 emissions through the intermediate variable of energy intensity because CEC could increase the cost of fossil energy consumption and then drive down coal consumption. More importantly, CEC should be included as one of the carbon management tools.

Spatial Effect of Coal Production on Energy Intensity

In China, the CEC standard is not determined according to the real amount of ecological value loss. Instead, it is determined by coal production. That is why we choose coal production as an explanatory variable. Another reason is that CEC will eventually affect coal production. We built a model that used coal prices (*lnEpr*) and industrial structure (*Ist*) as explanatory variables in order to simulate their impacts on energy intensity. **Table 9** shows the results of ordinary two-stage least squares (2SLS) and

TABLE 9 | Impact mechanism of coal production on energy intensity using 2SLS and GS2SLS.

	2SLS	GS2SLS
W·Ein		1.336***
		[0.311]
lnCpro	0.072***	0.543***
	[0.009]	[0.162]
lnEpr	0.275	0.023
	[0.189]	[0.121]
Ist	−0.185	−3.530***
	[0.371]	[0.862]
Constant	−1.272	−2.987***
	[1.151]	[0.944]
Hausman specification test	4.96**	−15.662***

*Notes: Standard errors are shown in brackets *p < 0.01, **p < 0.05, ***p < 0.1.*

TABLE 11 | Impact mechanism of coal production on energy intensity using GS2SLS by region.

	East	Central	West
W·Ein	1.394***	0.738	1.052***
	[0.270]	[0.866]	[0.395]
lnCpro	0.141**	0.558**	−0.562*
	[0.057]	[0.240]	[0.299]
lnEpr	−0.013	0.135	0.145
	[0.064]	[0.265]	[0.193]
Ist	−0.707	−3.362***	1.842
	[0.489]	[1.225]	[1.735]
Constant	−0.219	−4.031**	3.591
	[0.320]	[1.857]	[0.142]
Hausman specification test	−5.947	−10.174**	−8.435*

*Notes: Standard errors are shown in brackets *p < 0.01, **p < 0.05, ***p < 0.1.*

TABLE 10 | Statistical properties of CEC, *Ein*, and *Cpro* in different regions.

	Variables	Mean	Std.Dev	Minimum	Maximum	Observations
Est	CEC	276610.40	333742.60	0	1499751.00	99
	Ein	0.55	0.24	0.14	1.21	99
	Cpro	3023.42	4681.44	0	17667.60	99
Central	CEC	431716.80	476868.70	26931.20	2783452.00	81
	Ein	1.08	0.89	0.20	4.23	81
	Cpro	25025.21	34309.06	315.50	104190.90	81
West	CEC	322764.80	300433.00	15077.00	1583978.00	90
	Ein	1.15	0.68	0.34	3.52	90
	Cpro	10963.27	13175.97	425.45	57102.48	90

GS2SLS. The Hausman specification test (Hausman, 1978) of both 2SLS and GS2SLS showed that *lnCpro* is endogenous nationwide. CEC was chosen as the instrumental variable to substitute coal production to build 2SLS and GS2SLS model because it will negatively affect coal mining activities.

Table 9 indicates that the coefficient of the spatial lagged *Ein* was significant at the 1% level. It shows that energy intensity presents a significant spatial spillover effect. Besides, *lnCpro* displays a positive impact on energy intensity. Combining with the results in *Data Processing*, we can conclude that reducing coal production in the neighbor will reduce local CO_2 emissions. *Ist* negatively affected energy intensity. It indicates that the upgrading of the industrial structure in the neighbor will reduce the local CO_2 emissions. The result implies that the economic losses caused by the reduction in coal production should be partly accepted by the beneficiaries of CO_2 emission mitigation in neighboring provinces.

Because of the spatial heterogeneity of China's coal resource, the eastern region is traditionally known as the coal consumer, and the Western is the coal provider. However, CO_2 emissions are high to the east and low to west China (Long et al., 2016). Therefore, in order to determine the impact of coal production on energy intensity, a regression analysis was carried out considering the different regions (**Supplementary Figure S3**). The statistical characteristic values of the variables show that the CEC value ranks first in the central, whereas the Western has the highest energy intensity. All values in the eastern are significantly smaller than those in the central and west (**Table 10**). **Table 11** implies that (1) although the influence of coal production on energy intensity is significantly positive in the eastern region, the endogenous test showed that coal production and energy intensity did not display a mutual relationship. The possible reason is that although coal is also produced in the eastern, it is the traditionally net coal import area. Therefore, reducing coal production in the east cannot reduce energy intensity. Meanwhile, the industrial structure of the eastern has also an insignificant impact on energy intensity. The reason maybe is that the value of industrial structure in the eastern is relatively high; the potential for upgrading in the short term is not easy. In the short term, it is not feasible to reduce energy intensity by improving the industrial structure in the eastern region of China. (2) The spatial lagged *Ein* coefficient was not significant in the central. It indicates that there is no spatial correlation between energy intensity among provinces. However, both the reduction in coal production and the upgrading of the industrial structure can reduce the energy intensity in the local. It implies that the central region has the potential to reduce energy intensity. (3) The spatial lagged *Ein* coefficient for the west was significant, indicating that energy intensity in the west is positively correlated. The significantly negative correlation between coal production and energy intensity indicated that reducing coal mining will cause energy intensity to decrease. The Western characters as the net coal exporter require reducing coal supply to the east and the central. However, the pathways to reduce coal consumption in the eastern and the central should be different. The east should actively transform the energy structure and reduce the proportion of coal, whereas in the central, improving the industrial structure and reducing energy intensity can reduce the demand for coal. If coal demand and energy structure remain unchanged nationwide, even energy intensity decreases in central China caused by the reduction of coal production in the west will inevitably increase. In the west, renewable energies such as photovoltaics and wind power should be promoted to mitigate the pressure on coal production. Of course, adjusting the price gap between coal and alternative energies is the crux point. CEC could be considered an instrument. At the same time, the relatively advanced industries should be partly relocated from the east and the central to the west in order to reduce energy intensity in these regions.

Policy Implication

The spatial spillover effect of energy intensity and CEC implies that CEC policies should focus on its impact on the neighboring areas. Pigou tax can support our view, and CEC can be seen as a kind of tax that internalizes external effects. However, the focus of the Pigou tax is only on how to make up for the direct gap between private costs and social costs. It does not tell us that external effect charges will also produce spatial spillover effects. Because energy has cross-regional input and output, charging for the externals should pay more attention to the synergy between regions. And this article proves that external charges, that is, CEC has the spatial spillover effect of mitigating CO_2 emissions across provinces. The practical enlightenment of this article is as follows: (1) The goal of carbon neutrality is difficult to achieve only by relying on regulations and policies. The government should guide the market formation in the process of environmental governance. Ecological costs should be paid to internalize external costs. The increased prices will promote a decline in energy intensity and then mitigate CO_2 emissions. The CEC proposed in this article can be used as a marketable tool to achieve carbon neutrality. (2) Establishing the CEC mechanism is the crux to promoting the coordinated achievement of carbon neutral goals among regions. On the spatial scale, the interregional ecological compensation mechanism with spatial spillover effects can promote the alignment of carbon neutral actions between neighboring provinces, especially the developed provinces and energy resource endowment provinces. The spatial correlation proposed in this article provides the basis. (3) Ideas are provided for the development strategies of coal resources in different regions. Because of the uneven spatial distribution of coal resources and the various resource endowments of provinces, this article proposes coal resource-mining strategies suitable for regional characteristics.

In order to achieve carbon peak and carbon neutrality, we suggest that (1) the Chinese government increase CEC in order to reduce CO_2 emissions. (2) CEC should not be limited to the loss of ecological value itself or consider only one area. Policymakers should contemplate a national perspective. (3) In the process of implementing carbon quotas, the standards for non–coal-producing regions should be strengthened, whereas in coal-producing areas, they should be lessened. At the same time, non–coal-producing regions are encouraged to purchase quotas from coal-producing provinces to compensate for the economic losses of coal-producing regions due to coal production reduction. These will have a spatial spillover effect on CO_2 emission mitigation in the neighbor.

CONCLUSION

In this study, we used panel data of 30 Chinese provinces from 2009 to 2017 and different spatial econometric models to recover the spillover effect of CEC on CO_2 emissions. The results support the validity of the EKC hypothesis. Moreover, we determined that (1) reducing energy intensity will spatially mitigate CO_2 emissions. Likewise, CEC also presents a spillover effect on energy intensity. Thus, CEC is spatially related to CO_2 emissions. (2) Coal production positively affects energy intensity; industry structure negatively affects energy intensity. Reducing coal production and upgrading the industrial structure in the neighbor will mitigate local CO_2 emissions. (3) The regression analysis of the different regions indicated that interregional cooperation is necessary to reduce energy intensity. In addition, the east and the central should develop alternative energy to collaborate with the Western to reduce coal production and energy intensity. In the future, other developing countries that rely on resources for economic development should pay more attention to the impact and the spillover effects of ecological compensation on CO_2 emissions.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding authors.

AUTHOR CONTRIBUTIONS

SW: initial conceptualization, data collection and processing, methodology building, software application, writing-original draft. NB-O: conceptualization, discussion, supervision. JY: methodology guidance and software application. FC: writing-review, supervision, funding. YW: supervision. All authors contributed to the paper and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2021.778937/full#supplementary-material

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