Spatial Analysis of China Provincial-Level CO_2 Emission Intensity

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Abstract

This study offers a unique contribution to the literature by investigating the influential factors of energy-related carbon dioxide emission intensity among a panel of 30 provinces in China covering the period 1991-2010. We use novel spatial panel data models to analyze the drivers of energy-related emission intensity, which we posit are characterized by spatial dependence. Our results suggest: (1) emission intensities are negatively affected by per-capita, provincial-level GDP and population density; (2) emission intensities are positively affected by energy consumption structure and transportation structure; and (3) energy price has no effect on the emission intensities.

Keywords: CO_2 emissions intensity, spatial panel data models, China

JEL codes: Q43, Q53, Q54, Q56

1 INTRODUCTION

Understanding the geographic distribution of sources of carbon dioxide emissions (CO_2) can aid policy in combating climate change. The geographic distribution of emissions does not affect the climatic impact of greenhouse gas emissions, but the distribution of economic activity and energy consumption does affect local regions which are the source of emissions. Combating *global* climate change will require multilateral, international agreements, but the fight against *local* climate change causes will start at home.

This is particularly true in China which surpassed the US to become the largest aggregate emitter of CO_2 emissions in 2006. Since the market-oriented reforms of 1978, China, as a whole, has experienced remarkable economic growth accompanied by a very high demand for energy consumption. An analysis at a more disaggregated level reveals an imbalance in economic growth and energy consumption among different regions in China. For example in 2010, the GDP in Jiangsu accounted for over 3 trillion whereas Hainan accounted for less than 300 billion Chinese Yuan. These disparities also reveal themselves in terms of provincial-level CO_2 emissions. Therefore, in order to mitigate its own emissions, China must first have a look inward at the geographic distribution of the drivers of its emissions. Arguably, mitigation policies will come at the expense of economic growth in some or all regions of China, which in turn will affect the political economy of implementing such policies at the province and national level.

Past studies have found that the main factors driving China's environmental emissions are pressures from population, urbanization, industrialization, GDP per capita and energy intensity (Kambara, 1992; Fan et al., 2006; Hang and Tu, 2007; Ma and Stern, 2008; Lin et al., 2009; Li et al., 2011). These factors have a positive effect on emissions but the impact has been gradually declining over the past few decades (Lin et al., 2009). Other factors such as technological advancement, industrial sector and energy prices have also been identified as influencing China's CO_2 emissions (Li et al., 2011; Kambara, 1992; Ma and Stern, 2008; Hang and Tu, 2007).

A possible shortcoming of previous studies within this literature is that all assume that inter-jurisdiction regions to be cross-sectional independent and the spatial interaction effects are ignored. Anselin (1998) and LeSage and Pace (2009) point out that the a local region's characteristics may depend on its neighbors; therefore, ignoring spatial dependence would lead to model misspecification or create biased estimated parameters in an ordinary least squares (OLS) framework.

The importance of geography is captured in the argument for a "pollution displacement" hypothesis in which high-income regions are effectively exporting their pollution to low-income regions; or, one could argue that higher-income regions are inducing greater emissions by importing goods from these more energy intensive, lower-income regions. Geography has been identified as a major determinant of cross-country economic growth due to factors such as the diffusion of technology (Keller, 2004). One could argue that CO_2 emission intensity would decrease with technological improvements, so the diffusion of technology could possibly help improve neighboring environmental conditions. Geography is also important because environmental policies promulgated in one region might spill over into other neighboring regions (Markusen et al., 1995). Local governments, such as a province, likely assess policy against those of their neighbors in order to reduce the costs of decision-making. Hence, spatial interaction effects should be considered in the context of regression modeling.

Recognizing the importance of geography in China's CO_2 emissions, Auffhammer and Carson (2008) use a spatial econometrics model to forecast China's emissions using province-level information. The authors found that incorporating spatial dependence into their regression model, in general, improved forecasts. Despite their contribution however, the authors did not explore different data generating processes for the spatial dependence, nor did they offer a rigorous interpretation of the spatial impacts. These small deficiencies, therefore present a gap in the literature.

Comparing with the previous studies, this study offers four unique contributions to the literature by: (1) more explicitly considering and testing for the types of spatial dependence within the relationship; (2) using recently developed, spatial panel data models and diagnostics to determine the most appropriate spatial econometric model; (3) offering a more rigorous interpretation of both the direct and indirect (spillovers) spatial impacts; and, (4) extending the data to consider the years 1991-2010, which is important for capturing recent developments in provincial-level energy consumption and economic growth.

The rest of this manuscript is structured as follows. Section two offers a description of the data, model, and the explanatory variables. Section three discusses the spatial statistics. Section four introduces the spatial econometric techniques and the methodology. Section five discusses the estimation results. Finally, section six concludes this study and offers some policy suggestions.

2 DATA AND METHODOLOGICAL APPROACH

2.1 Data Sources

This paper uses a panel data of China's 30 provinces and municipalities for the period 1991-2010 (Hong Kong, Macao, Taiwan and Tibet are not included due to lack of data). First, CO_2 emission estimates for each province were obtained following the IPCC Guidelines (Intergovernmental Panel on Climate Change, 2006). These data were then used to calculate the units of CO_2 emission per unit GDP, which defines CO_2 emission intensity.

The explanatory variables include per-capita GDP, energy prices, population density, the ratio of coal consumption to total energy consumption, and the total length of highways. All of the variables are derived from the China Statistic Yearbooks and the provincial Statistical Yearbooks (CSY, 1992-2011).

The specific definition of each variable is provided here:

1. Per capita GDP (PCGDP): measured by the gross domestic product divided by the population. We hypothesize that economic growth is one of the most important factors in determining energy consumption and energy efficiency, which then exerts an influence on CO_2 emission intensity. Specifically, we hypothesize that per-capita GDP will reduce the CO_2 emission intensity.

2. Energy prices (EP): as in the standard economic law of demand, we hypothesize that energy prices are important a determinant of energy consumption. We predict that the energy price for a specific fossil fuel will be inversely related to the consumption of that fuel type; and since CO_2 is measured based upon energy consumption, we assert that energy prices will be inversely related CO_2 emission intensity.

3. Population density (PD): is measured as the population divided by the area. Theoretically, as China's population increasingly migrates to urban areas, which have greater access to modern energy technologies, we hypothesis a positive relationship between population density and CO_2 emission intensity. However, agglomeration effects can optimize the spatial allocation of production and energy resources which could improve production and energy efficiencies.

4. Ratio of coal consumption to total energy consumption (RCC): represented as the percentage of coal consumption of the total energy consumption. Since coal consumption accounted for the highest rate of total energy consumption in China (U.S. EIA, 2012), and the power transfer efficiency of coal is relatively lower than petroleum, natural gas and hydro power, we predict that the higher the ratio of coal consumption the higher the CO_2 emission intensity.

5. Total length of highways (TH): is measured as the total kilometers of paved highways at the province level in a particular year. The total length of highways serves as a proxy for activity in the transportation sector. The transportation sector in China accounts for a large portion of CO_2 emission intensity. Road transportation alone is consuming about half of the total energy used by the transport sector in China. Advances in technology have led to a reduction in certain pollution emissions, but the transportation sector is still the largest and fastest growing consumer of crude oil and the largest producer of CO_2 emissions produced from oil (Ministry of Transport, 2011). Thus, we expect an increase in the total length of highways will increase the CO_2 emission intensity.

2.2 Methodological Approach

We specify the regression model as follows:

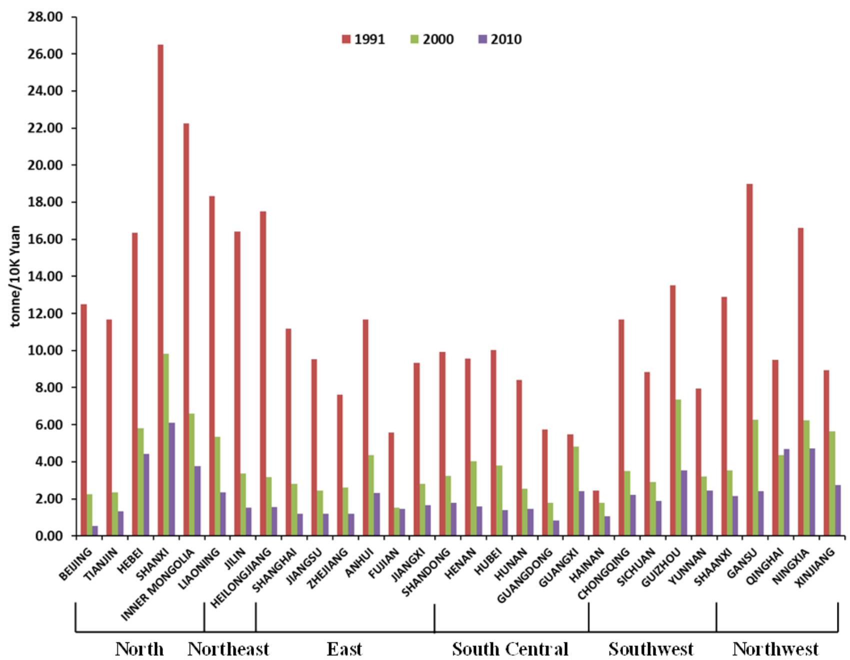
$$(1) \qquad CI_{it} = \beta_0 + \beta_1 PCGDP_{it} + \beta_2 EP_{it} + \beta_3 PD_{it} + \beta_4 RCC_{it} + \beta_5 TH_{it} + \mu_i + \eta_t + \varepsilon_{it}$$

where all variables are defined as natural logarithms in order to interpret the coefficients as elasticities. The parameter μ_i denotes the individual effect for each province and η_t denotes a common time effect. The individual effect can be interpreted as characteristics within provinces that do no change over time such as unobservable geographic characteristics. The time period effects control for time-specific shocks that affects all provinces in a given period of time; e.g., national policies that affect CO_2 emissions across all provinces in China.

3 SPATIAL STATISTICS

3.1 Overall Distribution

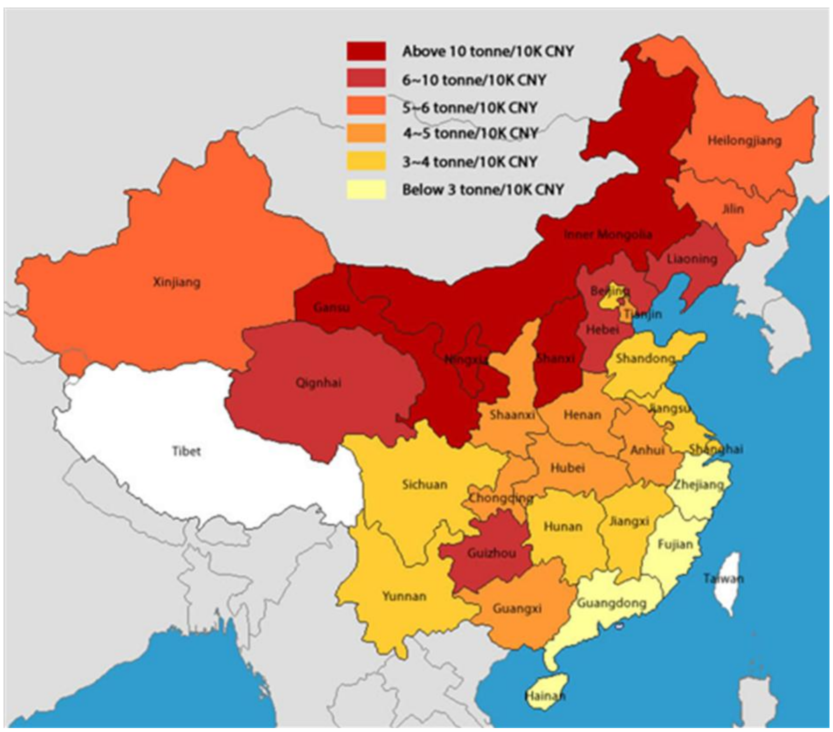
FIGURE 1. Provincial CO_2 emission intensity through time



We choose three points in time (1991, 2000, and 2010), to display China's provincial CO_2 emission intensity distribution, which shown in Figure 1. From

1991 to 2010, the CO_2 emission intensity of each province decreased year by year. The results show that provinces such as Shanxi and Ningxia consistently have the highest CO_2 emission intensities – their CO_2 emission intensities are almost six times higher than provinces such as Hainan and Guangdong. The disparity of CO_2 emission intensity shows a certain trend to spatial clustering. As displayed in Figure 2, the northern and western provinces are aggregated in terms of their high CO_2 emission intensities, and the southern and eastern provinces are generally aggregated in terms of their low CO_2 emission intensities. Figure 2 displays the average CO_2 emission intensities for 1991-2010.

FIGURE 2. Spatial distribution of average CO_2 emission intensity over the entire sample period



3.2 Global Spatial Autocorrelation

The global spatial autocorrelation of China's overall (energy-related) CO_2 emission intensity can be measured by Moran's I index. The formula for calculating global Moran's I index is

$$(2) \quad Moran's\ I = \frac{\sum_i \sum_j \omega_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{S^2 \sum_i \sum_j \omega_{ij}}; \quad S^2 = \frac{1}{n}\sum_i (Y_i - \bar{Y}); \quad \bar{Y} = \frac{1}{n}\sum_i Y_i$$

where Y_i and Y_j represent CO_2 emission intensity of province i and j, respectively. The term ω_{ij} denotes the element in the i^{th} row and j^{th} column of the spatial weight matrix. The spatial weight matrix is a compact reflection of the geographic relationship among different provinces. In this study, we choose the binary contiguity matrix, which is determined by observing whether the regions share a common border. The elements of the spatial weight matrix are defined as: if two regions i and j are neighbors, then the matrix elements ω_{ij} = 1 and ω_{ij} = 0 otherwise. Consistent with the literature, we normalize the spatial weight matrix according to row standardization (LeSage and Pace, 2009). That is, the sum of elements ω_{ij} in each row equals one. Row standardization allows us to interpret spatial spillover effects as an average of all neighbors.

The global Moran's I index is defined over the interval [-1, 1]. Positive Moran's I values imply positive spatial autocorrelation (or spatial dependence), where a value of one indicates perfect correlation. Conversely, negative values imply negative autocorrelation, where a value of negative one indicates perfect dispersion. A zero value indicates a random spatial pattern. The significance of Global Moran's I index can be tested by standard z-statistics.

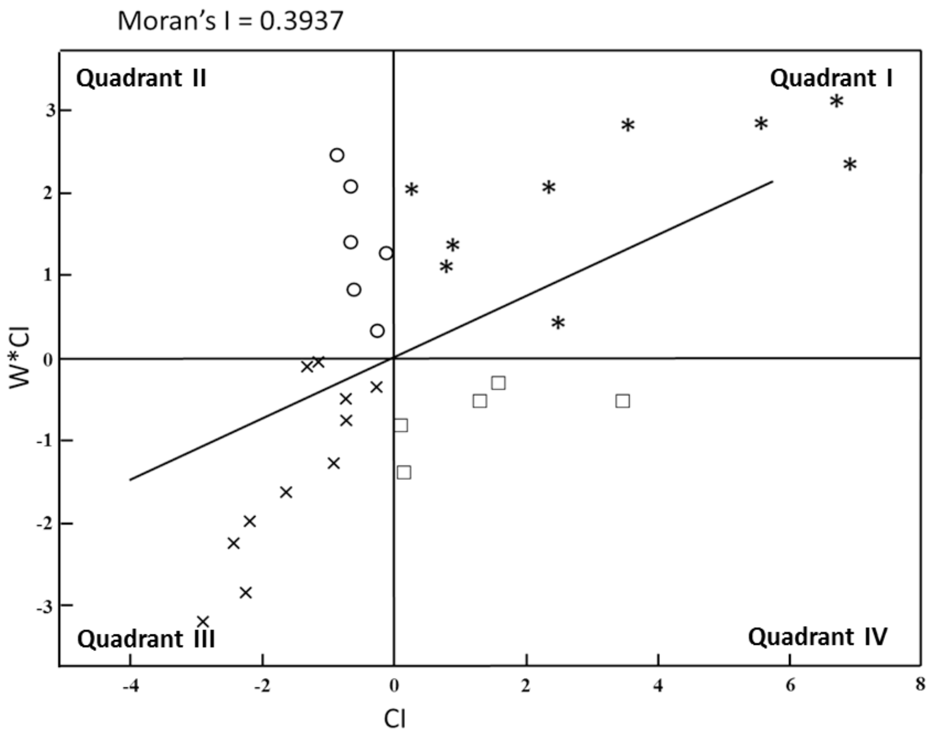
In this study, the overall Moran's I over a twenty year period is calculated as 0.394, which indicates positive spatial correlation at the one percent significance level. This indicates that China's carbon dioxide emission intensity tend to cluster together. Specifically, the provinces with high carbon dioxide emission intensities have a tendency to cluster together, whereas the provinces with low carbon dioxide emission intensities cluster together. Despite our findings of the spatial autocorrelation of CO_2 emission intensity, the Moran's I test only assesses the overall pattern and trend, and Moran's I is only effective when the spatial pattern is consistent across the provinces. If some of the provinces have positive spatial autocorrelation while others have negative spatial autocorrelation, then the effects could offset one other. In which case, the global Moran's I test may reveal non-spatial autocorrelation characteristics.

To further examine the clustering of among provinces, we employ a Moran's I scatterplot displayed in Figure 3. In this scatterplot, the horizontal axis refers to the deviation of provincial average carbon dioxide emission intensity from 1991 to 2010, whereas the vertical axis refers to the spatial lags of the deviation of the average carbon dioxide emission intensity. We calculate the spatial lags by using a first-order contiguity spatial weight matrix, which produces an average measure of carbon dioxide emission intensity among neighboring provinces. The four quadrants in the scatter plot depict: the quadrant I (the star points) is the HH clustering, which means provinces with high CO_2 emission intensity are associated with neighboring province with high CO_2 emission intensity; the quadrant II (the circle points) is the LH clustering, which means provinces with low CO_2 emission intensity are associated with neighboring province with high CO_2 emission intensity; the quadrant III (the cross points) is the LL clustering; and the quadrant IV (the square points) is the HL clustering.

The results in Figure 3 also imply that during this period of analysis, 63.33% (19 provinces) show similar characteristics of spatial autocorrelation. Further, 30% (nine provinces) in quadrant I and 33.33% (ten provinces) in quadrant III demonstrate similar characteristics of positive spatial autocorrelation. On the other side, 20% (six provinces) in quadrant II and 16.67% (five provinces) in quadrant IV demonstrate negative spatial autocorrelation. This means that the spatial autocorrelation and dispersion of provincial CO_2 emission intensity exist at the same time.

The statistically significant, spatial autocorrelation among provinces implies that standard ordinary least squares regressions of the drivers of emission intensities may lead to significant bias in regression results. Therefore, we posit a spatial panel data model to analyze the drivers of emission intensities at the provincial level in China.

FIGURE 3. Moran Scatterplot of Provincial CO_2 emission intensity



4 SPATIAL ECONOMETRIC MODELS

Spatial relationships can be modeled in a variety of ways depending on the relationship between the dependent variable and the explanatory variables. Following Elhorst (2012), there are three basic models that are used to estimate the spatial panel data models. All of the spatial econometric models can be grouped by the following equation

$$
\begin{aligned}
Y_{it} &= \rho \sum_{j=1}^{N} W_{ij} Y_{jt} + X_{it}\beta + \sum_{j=1}^{N} W_{ij} X_{ijt}\gamma + \mu_i + \eta_t + \phi_{it} \\
\phi_{it} &= \lambda \sum_{j=1}^{N} W_{ij} \phi_{it} + \varepsilon_{it},
\end{aligned} \tag{3}
$$

where Y_{it} denotes the dependent variable (CO_2 emission intensity) for the cross-sectional unit i at time t ($i = 1,...,N; t = 1,...,T$). X_{it} is a matrix of observations on the explanatory variables. The parameter β is a column vector of regression coefficients. The parameter ρ denotes the scalar spatial autoregressive parameter on the dependent variable, λ denotes the spatial autocorrelation coefficient on the error term, and γ is a (K×1) vector of spatial autocorrelation coefficients on the explanatory variables. The error term, ε_{it}, is assumed to be independently and identically distributed with a zero mean and variance σ^2.

The term $\sum_j W_{ij} Y_{jt}$ denotes the interaction effect of the dependent variable Y_{it} with the dependent variables Y_{jt} in neighboring provinces, where W_{ij} is the *i, j-th* element of a pre-specified nonnegative (N×N) spatial weighting matrix *W*. $\sum W_{ij} X_{ijt}$ denotes the weighted average effects of the neighboring provinces on the independent variables; and $\sum W_{ij} \phi_{it}$ denotes the weighted average effects of the neighboring provinces on the error terms.

The restriction of the parameters within Equation (3) defines the specific type of spatial panel model used. One, the spatial autoregressive model (SAR) is obtained by restricting both $\gamma = 0$ and $\lambda = 0$ – this model exhibits spatial dependence within only the dependent variable. Two, the spatial error model (SEM) is obtained by restricting both $\rho = 0$ and $\gamma = 0$ – this model exhibits spatial dependence within only the error terms. Three, the spatial Durbin model

(SDM) is obtained by restricting $\lambda = 0$ – this model allows for spatial dependence within both the dependent variable and the independent variables. Finally, if all the parameters with the exception of β are restricted, then the model reduces to the traditional panel data model with two-way fixed effects.

In this study, we follow the specification tests outlined in Elhorst (2012). The first step is to test the standard, non-spatial panel models against the SAR and SEM models by employing a series of Lagrange Multiplier (LM) tests. The second step is to investigate the joint significance of spatial fixed effects and time-period fixed effects by using the Likelihood ratio (LR) tests. If we fail to reject the spatial model in the previous step, then the third step will be to test whether the SDM model can be simplified to the SAR or SEM model.

The hypothesis tests for the third step are

$$H0: \gamma = 0 \tag{4}$$

$$H0: \gamma + \rho\beta = 0 \tag{5}$$

H0: $\gamma = 0$ examines whether the SDM model can be simplified to the SAR model, and H0: $\gamma + \rho\beta = 0$ examines whether it can be simplified to the SEM model (Elhorst, 2012). Both tests follow a chi-squared distribution. A rejection of both hypotheses suggests that the SDM model provides the best fit to the data. Conversely, a failure to reject (4) suggests that the SAR model best describes the data, which can be balanced against the results of the (robust) LM tests for the spatial autoregressive model. Similarly, a failure to reject (5) suggests that the

SEM model best describes the data – which can also be balanced against the results of the (robust) LM tests for the spatial error model.

The last step is to estimate the spatial spillover effects of CO_2 emission intensity. We follow LeSage and Pace (2009) by estimating the direct and indirect effects of the explanatory variables. Direct effects estimates measure the impact of changing an independent variable on the dependent variable of a spatial unit and the indirect effects estimates measure the impact of changing an independent variable in a particular unit on the dependent variable of all other units.

5 ESTIMATION RESULTS

The estimation results for the non-spatial panel data models are reported in Table 1. Columns (1) through (4) represent the estimation results of pooled OLS, spatial fixed effects only, time-period fixed effects only, and spatial and time-period fixed effects, respectively.

When using the classical LM tests, both the hypothesis of no spatially lagged dependent variable and the hypothesis of no spatially autocorrelated error term are strongly rejected at a one percent significance level with the exception of including both the spatial and time-period fixed effects. When using the robust LM tests, the hypothesis of no spatially lagged dependent variable is still rejected at a one percent significance level for each of the specifications. The hypothesis of no spatial autocorrelated error term is rejected at one percent significance level when spatial fixed effects are included and five percent significance level when the time-period fixed effects are included. But this same hypothesis (robust LM spatial error) cannot be rejected for the pooled OLS. These results seem to imply that the SAR model is a more appropriate specification than the non-spatial model as we find fairly consistent evidence across all models to reject the null hypothesis of no spatial lag. We find mixed results to reject the hypothesis for spatially autocorrelated error term.

TABLE 1. Estimation results of non-spatial panel data models

Determinants	Pooled OLS	Spatial Fixed effects	Time-period fixed effects	Spatial and time-period fixed effects
PCGDP	-0.413***	-0.642***	-0.366***	-0.755***
	(-23.038)	(-21.822)	(-10.382)	(-7.466)
EP	0.476**	0.427***	-0.255	0.199
	(2.574)	(3.737)	(-0.743)	(0.896)
PD	-0.180***	-1.007***	-0.193***	-1.153***
	(-13.119)	(-5.328)	(-14.163)	(-5.610)
RCC	1.036***	0.149	1.061***	0.080
	(16.188)	(1.441)	(17.068)	(0.806)
TH	-0.226***	0.207***	-0.228***	0.056
	(-12.414)	(5.032)	(-10.362)	(1.035)
Intercept	5.683***	NA	NA	NA
	(6.229)			
σ^2	0.137	0.049	0.123	0.044
R^2	0.723	0.900	0.751	0.912
Log Like	-251.420	55.585	-219.016	91.450
Sample	600	600	600	600
LM Spatial lag	94.862***	60.1405***	26.821***	0.876
Robust LM Spatial lag	57.297***	71.2093***	32.183***	7.692***
LM Spatial error	37.572***	15.2978***	5.624**	0.062
Robust LM Spatial error	0.007	26.3666***	10.986***	6.878***

Note: All variables are measured as natural logs. The symbols ***, ** and * denote a one, five and ten percent significance level, respectively. Numbers in the parentheses represent t-test values.

To investigate the joint significance of the fixed effects and time-period fixed effects, we perform the LR tests. The null hypothesis that the spatial fixed effects are jointly insignificant is rejected at a one percent level (620.9317, with 30 degrees of freedom, $p < 0.01$), and the null hypothesis that the time-period fixed effects are jointly insignificant is also rejected at a one percent level (71.7303, with 20 degrees of freedom, $p < 0.01$). These test results seem to justify the extension of the model with the two-way fixed effects model– i.e., include both the fixed effects and time-period fixed effects.

We also conduct a Hausman test to further test the correct panel data specification between a fixed effects and random effects model. The Hausman test results (44.6832, with 11 degrees of freedom, $p < 0.01$) imply that the fixed effects model is the more appropriate specification. Table 2 gives the estimation results of CO_2 emission intensity according to the three spatial specification panel data models.

Since the Lagrange Multiplier test results suggest that the spatial models are a more appropriate specification than the non-spatial models, we will continue to test which spatial model offers the best fit for the data. We perform both the Wald test and LR test to test the hypothesis whether the SDM model could be simplified to the SAR model or SEM model. According to the Wald test result (105.233, with 5 degree freedom, $p < 0.01$) and LR test result (125.952, with 5 degree freedom, $p < 0.01$), the null hypothesis (4) that the SDM model can be simplified to the SAR model is rejected at a one percent significance level. Similarly, the null hypothesis (5) that the SDM model can be simplified to a SEM model is also rejected at a one percent significance level based on the Wald test result (117.640, with 5 degree freedom, $p < 0.01$) and LR test result (112.906, with 5 degree freedom, $p < 0.01$). These results imply that both the spatial lag model and spatial error model are rejected in favor of the spatial Durbin model. Therefore, we conduct a sensitivity analysis of the SDM model by comparing the estimation results to the SAR and SEM model (all models are estimated with both the fixed and time-period fixed effects).

TABLE 2. Estimation results of spatial panel data models

Determinants	SAR		SEM		SDM	
PCGDP	-0.640***	(-6.300)	-0.749***	(-7.118)	-0.519***	(-5.073)
EP	0.142	(0.639)	0.204	(0.888)	0.106	(0.491)
PD	-1.146***	(-5.550)	-1.165***	(-5.440)	-1.282***	(-5.941)
RCC	0.124	(1.243)	0.083	(0.809)	0.257***	(2.624)
TH	0.073	(1.341)	0.054	(0.962)	0.150***	(2.748)
ρ	0.342***	(7.175)	NA		0.106**	(1.950)
λ	NA		0.094*	(1.658)	NA	
W*PCGDP	NA		NA		-0.702***	(-8.247)
W*EP	NA		NA		0.203	(0.552)
W*PD	NA		NA		1.062***	(2.656)
W*RCC	NA		NA		-0.343*	(-1.802)
W*TH	NA		NA		0.275**	(2.362)
σ^2	0.044		0.047		0.039	
R^2	0.918		0.912		0.927	
Sample	600		600		600	
Log Like	84.973		91.496		147.949	

Note: All variables are measured as natural logs. The symbols ***, ** and * denote a one, five and ten percent significance level, respectively. Numbers in the parentheses represent t-test values.

As can be gleaned from the estimated results in Table 2, the coefficients of independent variables are basically consistent with the theoretical expectations offered in section 2.1. Just focusing on the SDM coefficient estimates, an interpretation of the coefficient on per-capita GDP is that a ten percent increase of per-capita GDP is associated with 5.19% decrease of the CO_2 emission intensity (holding all else constant). An interpretation of the ratio of coal consumption to total energy consumption is that a ten percent decrease will lead to a 2.57% decrease in emission intensity. Similarly, the total length of highways coefficient implies that a ten percent increase will lead to 1.5% increase of CO_2 emission intensity. The results also suggest that a ten percent increase in population density is associated with 12.82% decrease of the CO_2 emission intensity, which implies that agglomeration effects are leading to an improvement in energy efficiency which in turn reduces emission intensity. Contrary to expectations, we do not find a significant relationship between energy prices and CO_2 emission intensity, which implies that energy prices do not play a role in reducing CO_2 emission intensity. A possible explanation for this lack of statistical significance is that the Chinese government subsidizes energy prices thereby keeping prices artificially below the market price.

Following LeSage and Pace (2009), we estimate the direct and indirect effects to yield an interpretation of the spatial spillover effects. The direct and indirect effects of each explanatory variable are reported in Table 3. The difference between the direct effects in Table 3 and the coefficient estimates in Table 2 are due to the feedback effects that arise as a result of impacts passing through neighboring provinces and back to the provinces themselves. The feedback effects include both the impacts from the spatially lagged dependent variable ($\rho \sum W_{ij} Y_{jt}$) and the impacts from the spatially lagged value of the explanatory variable itself ($\sum W_{ij} X_{jt} \gamma$).

TABLE 3. Direct & Indirect effects of SDM model

Determinants	Direct Effect		Indirect Effect		Total Effect	
PCGDP	-0.533***	(-5.412)	-0.827***	(-7.594)	-1.360***	(-9.626)
EP	0.105	(0.466)	0.231	(0.536)	0.336	(0.697)
PD	-1.252***	(-5.738)	1.002**	(2.278)	-0.250	(-0.581)
RCC	0.247**	(2.410)	-0.353	(-1.728)	-0.106	(-0.461)
TH	0.157***	(2.934)	0.310**	(2.457)	0.467***	(3.463)

Note: All variables are measured as natural logs. The symbols ***, ** and * denote a one, five and ten percent significance level, respectively. Numbers in the parentheses represent t-test values.

The results in Table 3 reveal that the direct effects of all the explanatory variables (with the exception of energy prices) are statistically significant, and three of the explanatory variables have significant indirect effects. The statistically significant coefficients on both the direct effect and indirect effect of per-capita GDP are negative which implies that the own-province per-capita GDP increases will reduce the CO_2 emission intensity of both own province and neighboring provinces. The coefficients of both the direct effect and indirect effect of total length of highways are positive and significant, and the coefficients imply that an increase in own province highway construction leads to an increase of both own province and neighboring province CO_2 emission intensity. The negative coefficient of direct effect and positive coefficient of indirect effect of population density imply that own-province population density increases will decrease the CO_2 emission intensity of own province but increase the CO_2 emission intensity of neighboring provinces.

6 CONCLUSION AND POLICY IMPLICATIONS

In this paper, we analyzed the influence of economic activity, energy prices, population density, energy consumption structure, and transportation structure on CO_2 emission intensity in China. We used spatial econometrics methods so as to avoid the potential coefficient bias from ignoring spatial autocorrelation as in OLS estimation.

Our regression results suggest that: (1) per-capita GDP reduces CO_2 emission intensity, which implies that promoting the local economic development, may help to reduce CO_2 emission intensity; (2) population density decreases the CO_2 emission intensity, which suggests that population concentration, could improve the production efficiency and energy efficiency so as to decrease the CO_2 emission intensity; (3) an increase in the ratio of coal consumption to total energy consumption significantly leads to a significant increase in the CO_2 emission intensity; (4) an increase in the total length of highways leads to an increase of the CO_2 emission intensity; (5) energy prices in China have no significant effect on the CO_2 emission intensity.

Based on the analysis, we provide some policy suggestions that: (1) targeting an increase per capita GDP but weigh such targets with policies to reduce emission intensity since economic development can still be compatible CO_2 emission mitigation; (2) increasing population density with population control to decrease emission intensity since population density leads to agglomeration effects; (3) encouraging the development of less carbon-intensive energy resources such as natural gas or renewables to replace the coal consumption; (4) improving governmental fuel efficiency standards to reduce emission intensity in the transportation sector; (5) reducing artificial price distortions so that the energy prices more accurately reflects the true market cost.

The significance of the indirect effects suggest that the Chinese government should promote the sharing and exchange of information and technology across provinces, and develop appropriate policies to strengthen cross-province development.

This study suffers from some limitations including the problem of measurement error. Our measure of carbon dioxide emissions, which is consistent with the rest of literature, is based upon the consumption of energy, so it subjects to mismeasurement. An additional problem is that we specified a single equation, reduced-form model, not a structural model. Although these reduced-form models are used fairly frequently in the energy literature, they can offer limited information for policy decisions because such models ignore issues such as inter-fuel substitution, technical change, and changes in supply (Bhattacharyya, 2011).

Further research may consider variables that indicate the likelihood of a province adopting cutbacks in energy emissions. Due to data limitations we did not explore this variable within this study.

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