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Abstract Is emission intensity of carbon dioxide (CO_2) spatially correlated? What determines the CO_2 intensity at a provincial level? More importantly, what climate and economic policy decisions should the China's central and local governments make to reduce the CO_2 intensity and prevent the environmental pollution given that China has been the largest emitter of CO_2? We aim to address these questions in this study by applying a dynamic spatial system-GMM (generalized method of moment) technique. Our analysis suggests that provinces are influenced by their neighbours. In addition, CO_2 intensities are relatively higher in the western and middle areas, and that the spatial agglomeration effect of the provincial CO_2 intensity is obvious. Our analysis also shows that CO_2 intensity is nonlinearly related to GDP (gross domestic product), positively associated with secondary-sector share and FDI (foreign direct investment), and negatively associated with population size. Important policy implications are drawn on reducing carbon intensity.

Keywords: Carbon intensity, Environmental Kuznets curve, Dynamic spatial panel

1 Introduction

Economists, ecologists, private industries and government decision-makers have long been interested in the relationship between economic growth and environmental quality (Burnett and Bergstrom, 2010). China has experienced a consistent and rapid economic growth since the economic reforms started in 1978. However, the pressure from energy constraints and environmental pollution has been increasingly serious over the same time period. In recent years, scholars have extended the study of pollutants from the regular pollutants (say, sulphur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), and particulate matters) to carbon dioxide (CO_2), which has become the main driving force of global climate changes. Especially, the increased demand for energy in China has generated concomitant increase of carbon emissions, mainly measured by CO_2 emissions in this study, which poses an unprecedented challenge to China's, and even global, environment and sustainable development (Liu et al., 2010). China has been one of bigger contributors to the rapid growth of global CO_2 emissions, accounting for 44% of the increase in global CO_2 emissions in 1990-2004 (Kahrl and David, 2006). In 2007, the CO_2 emissions ratio in China (defined as the total CO_2 emissions of China to that of the world) hit the historical highest level of 21.01% and simultaneously, China surpassed the United States for the first time to become the largest CO_2 emitter in the world with total CO_2 emissions of 6.28 billion metric tons (Zheng et al., 2011). The Intergovernmental Panel on Climate Change (IPCC) (2007) report indicates the fact that the most important environmental problem of our ages is global warming. The predicted effects of global warming include melting of the polar ice caps, flooding of coastlines, severe storms, changes in precipitation patterns, and widespread changes in the existing ecological balance (Lindsay, 2001). The ever increasing amount of CO_2 emissions seems to be intensifying this problem (Soytas and Sari, 2009; Narayan and Narayan, 2010).

To resolve the contradictions between economic development and the above mentioned energy consumption and environmental pollution problems, the 18th National Congress' report includes three important development concepts: the green development, the circular development, and the low-carbon development.[1] One effective way to achieve the goal of low-carbon development in China is to reduce the industrial CO_2 intensity (CO_2 emissions per unit of gross domestic product (GDP). This raises the following question: what factors determine the CO_2 emission and its change? After reviewing a bunch of literature, Liu et al. (2010) concluded that China's economic growth and energy intensity are two important factors to affect the change of China's carbon emissions or carbon intensity.

[1] The National Congress of the Communist Party of China, which is held once every five years, is the highest body within the Communist Party of China. The 18th National Congress was held in November 2012 in Beijing.

Besides, average labour productivity in the industrial sectors (Wu et al., 2005), economic scale (Wu et al., 2006), fuel mix (Wang et al., 2005; Wu et al., 2006), renewable energy penetration (Wang et al., 2005), final-energy-mix, and industry structure (Fan et al., 2007) are also important contributors to CO_2 emissions and CO_2 intensity.

Existing studies on CO_2 intensity are mainly based on the environmental Kuznets curve (EKC) model, which focuses the relationship between pollutant emissions and income/GDP (Grossman and Krueger, 1991; Panayotou, 1993; Schmalensee et al., 1998; Friedl and Getzner, 2003; Cai, 2008; Lin and Jiang, 2009). Roberts and Grimes (1997) and Costantini and Martini (2006) modified the EKC model and analysed the evolution and determinants of CO_2 intensity across countries with different income levels. However, the classic EKC model has been criticized because of the following drawbacks: first, it does not consider the impacts of factors other than the economic growth on the pollutant emissions, so it fails to explain the CO_2 intensity comprehensively. Dasgupta et al. (2002), Dinda (2004), and Stern (2004) pointed out that more explanatory variables and policies should be included when studying how to reduce CO_2 emissions. Thus, the aforementioned studies in the first paragraph have considered quite a few other determinants besides the economic growth. Second, the hypothesis of the EKC model ignores the spatial-temporal characteristics within the data. By ignoring the temporal aspect, spurious results or misleading conclusions (misspecified t and F statistics) could be generated. By ignoring the spatial aspects, biased or inconsistent estimators could be generated because the existence of transboundary CO_2 emissions between neighbours (Burnett and Bergstrom, 2010).

Studies on China CO_2 intensity at national, regional, or sector level are few. At sector level, Chen (2011) decomposed the CO_2 intensity changes using 2-digit industry data in China and found that first, the main and direct reason for the downward fluctuation of CO_2 intensity is the reduction in energy intensity or the improvement in energy productivity and second, energy structure and industrial composition have positive effects on CO_2 intensity reduction. At provincial level, Zeng and Pang (2009) found that the ranking of the provinces in terms of total CO_2 emissions did not change much between 2000 and 2007. They pointed out that the provinces whose economic transition starts relatively earlier attain better effects from CO_2 emission reduction, and that CO_2 emissions in some provinces have a low total amount whilst with a rising trend. By estimating the CO_2 emissions from fossil energy consumption in 30 provincial units in China between 1997 and 2007, Du et al. (2010) found that 29 provinces, except Beijing, show an increasing trend in per capita CO_2 intensity. Yue et al. (2010) analysed the provincial CO_2 emissions, per capita CO_2 emissions and CO_2 intensity in China between 1995 and 2007 and found that CO_2 intensity in the middle and western areas is far higher than that in the eastern areas. Yu et al. (2011) studied the determinants of CO_2 intensity in China using a panel data set of 29 provincial units from 1995 to 2007. Using a feasible generalized least squares (FGLS) method, they find that there exists a nonlinear, inverted *N* relationship between CO_2 emission and GDP. However, their model contains only two explanatory variables: economic scale (i.e., per capita GDP) and economic structure (i.e., added value of secondary industry to GDP ratio).

At regional level, Liu and Zhao (2012) pointed out that the regional distribution of CO_2 intensity is obviously unbalanced and the regional differences in CO_2 intensity have been increasing slightly overtime. Fan and Liu (2012) analysed the regional distribution of CO_2 intensity between 1997 and 2008. They found that CO_2 intensity is directly related to the degree of industrialization and the adjustment in industrial composition in each province, and that the CO_2 intensity in east developed areas is much lower than that in other areas. Applying the Theil index and the spatial autocorrelation method, Zhao et al. (2011) found that the CO_2 intensity in eight comprehensive economic zones from 1999 to 2007 can be classified into three clusters: eastern and southern areas have the lowest level of CO_2 intensity; north-eastern areas, the middle reach of the Yellow River, and north-western areas have the highest level of carbon intensity; and the CO_2 intensity of the middle reach of the Yangtze River and the south-western areas is in the middle level.[2] The aforementioned studies analyse the issue of CO_2 emissions in terms of provincial level, but they fail to take into account the potential spatial dependence, i.e., neighbouring areas' CO_2 intensity could impact on the local CO_2 intensity.

Spatial dependence may occur in CO_2 intensities for at least three reasons. First, almost all spatial data have the characteristic of spatial dependence (Anselin, 1991), so do the provincial CO_2 emission intensity data. Second, in normal temperature and pressure, the mobility nature of CO_2 (as one kind of gas) makes it spread through the atmosphere, especially in the wind seasons, which determines the spatial dependence of CO_2 intensity. Third, as China has been speeding up the regional integration process, which promotes the communication and cooperation between regions. Driving by the catch-up effect and attracting by the lower cost, provinces get to learn from advanced provinces, especially those from their neighbouring area. As a result, the industrial structures across regions that are geographically proximate to each other get greater similar and the technologies attainable to them tend to be the same. The environmental quality, specifically the CO_2 intensity, has largely depended on the

[2] The eight comprehensive economic zones (CEZ) are, North-west CEZ, Middle Reach of Yellow River CEZ, North-east CEZ, South-west CEZ, Middle Reach of Yangtze River CEZ, North Coastal CEZ, East Coastal CEZ, and South Coastal CEZ.

proportion of industrial products in the gross provincial products and the technology levels applied in industrial production. Thus, if the spatial nexus is ignored, the coefficient estimates of the EKC model can be biased and inconsistent due to omitted variable bias.

The objective of this paper is to empirically examine the spatial nexus of provincial CO_2 intensity in China and the driving forces of it when the spatial nexus effect is controlled, using a panel data set of 30 provincial units from 1998 to 2010. Our primary interest lies in addressing the following questions: (1) Is the provincial CO_2 intensity spatially correlated? (2) What are the determinants of CO_2 intensity when the spatial dependence is taken into account? These questions are important for China's policy makers to understand better about the characteristics of provincial carbon emissions as well as CO_2 intensity, but the more important question is (3) what climate and economic policy decisions should the central and local governments draw up to reduce the CO_2 intensity and prevent the environmental pollution?

This study contributes to the existing literature in two respects. First, different from most of the existing studies which focus on CO_2 density (i.e., per capita CO_2 emissions), total emissions, or ambient levels of CO_2, we study the association between CO_2 emissions and economic development in China from the perspective of CO_2 intensity (CO_2 emissions per gross domestic product (GDP)). Tisdell (2001) pointed out that total emissions can still increase even when emissions per unit of GDP deceases, indicating that the scale effect of economic growth outweighs the composition effect and the technological effect due to higher productive efficiency (Panayotou, 2000). It is well recognised that the reduction in total CO_2 emissions or per capita CO_2 emissions is an important environmental indicator. However, China is a developing country in the period of high-speed industrialization development. Although China has engaged in adjusting industrial composition and transiting to the tertiarisation production, such fact cannot be ignored. As most developed economies has suffered, developing countries in this stage have to face a dilemma whether to maintain a high-speed economic growth and endure a certain degree of environmental degradation or to slow down economic development and concentrate on environmental pollution. There is no standard correct answer to this problem. It is necessary to protect the environment, but development and employment are also tasks of top priority in current China. Thus, considering the special stage where China stays, we propose that governments should pay more attention to the CO_2 emissions per unit of GDP besides the reduction of total CO_2 emissions or per capita CO_2 emissions. Moreover, China's central government targets the reduction of CO_2 intensity as the medium-term environmental protection mission. It announced a binding target in 2009 to reduce its carbon intensity by 40–45% by the end of 2020 compared to that in 2005. However, the relationship between economic growth and CO_2 intensity (a particular important indicator in China) has rarely been analysed by previous studies.[3] This paper aims at filling in this gap. Second, to the best of our knowledge, this is the first study attempts to examine the driving forces and spatial nexus of CO_2 intensity using the dynamic spatial panel data model, which differs from the traditional static or dynamic panel data model by taking into account both the dynamic and spatial effects of CO_2 intensity. Elhorst (2012) pointed out that either the dynamic but non-spatial or spatial but non-dynamic panel data models produce biased estimates.

The paper is organized as follows. Section 2 presents some stylized facts about the regional distribution of CO_2 emissions in China; Section 3 specifies a dynamic spatial econometric model of CO_2 intensity where some potential key explanatory variables, such as economic development, industrial composition, and technology, are identified. In addition, diagnostic tests and estimation strategies that help to choose the most appropriate model are introduced; Section 4 describes the data sources; Section 5 reports the empirical results; Finally, the last section summarizes the main findings and draws policy implications.

2 Some Stylized Facts

As a participant in the Copenhagen Accord, China announced a binding target in 2009 to reduce its carbon intensity by 40–45% by the end of 2020 compared to that in 2005. To achieve this goal, all provinces in China should dedicate to saving energy and reducing CO_2 emissions. However, natural resources are distributed unevenly across provinces. Various resource endowments together with regional variations in social-economic conditions and unbalanced regional economic development lead to different levels of CO_2 intensity across provinces. Descriptive statistics show that the regional distribution of CO_2 intensity in China is dramatically uneven. Generally speaking, from 1998 to 2010, CO_2 intensity increases sharply from the eastern coastal areas to the middle and western areas (Figure 1). In detail, six provinces with the lowest CO_2 intensities were Guangdong (0.111 tons/billion *yuan*), Hainan (0.115 tons/billion *yuan*), Fujian (0.116 tons/billion *yuan*), Beijing (0.134 tons/billion *yuan*), Guangxi (0.153 tons/billion *yuan*), and Zhejiang (0.158 tons/billion *yuan*); whereas six provinces with the highest CO_2 intensities were Gansu (0.533 tons/billion *yuan*), Qinghai (0.536 tons/billion *yuan*), Inner Mongolia (0.565 tons/billion *yuan*), Ningxia (0.664 tons/billion *yuan*), Guizhou (0.706

[3] Roberts and Grimes (1997) is the only work we know that studies the connection of carbon intensity and economic development during 1962-1991 for over 100 countries.

tons/billion *yuan*), and Shanxi (1.034 tons/billion *yuan*).[4] Hence, examining the provincial variations of CO_2 intensity and identifying its driving forces are necessary to make and implement effective and appropriate CO_2 reduction policies.

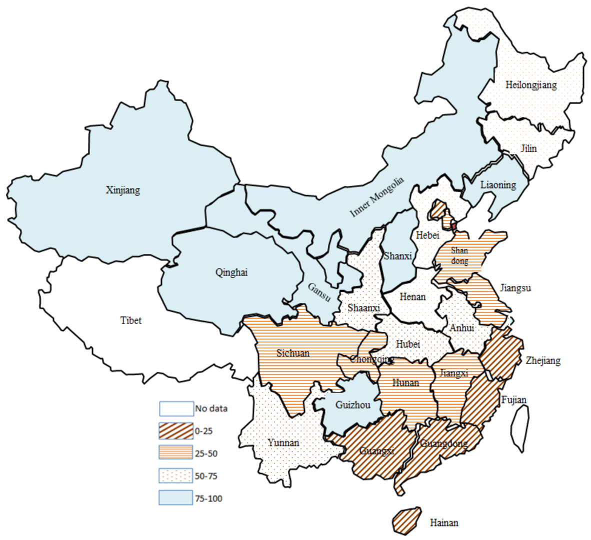

Fig. 1 The distribution of provincial average CO_2 intensities in China between 1998 and 2010

***Note:* The CO_2 intensity data are compiled from the database of Energy Economic Center at Renmin University of China (http://rucee.ruc.edu.cn)**

Observing Figure 2 that shows the changes in provincial CO_2 intensities in China during the same time period from 1998 to 2010, five patterns can be summarized. First, the CO_2 intensity was unevenly distributed across regions. It was relatively higher in the western and middle areas than in the eastern areas, partly because most of the high energy-intensive industries were located in the western and middle areas.

Second, the CO_2 intensity evolved over time. It went down slightly during the period of 1995–2002 compared to the period of 2003–2007 and dropped further in the period of 2008-2010. The overall declining trend of CO_2 intensity may imply that the CO_2 emission reduction policies and measures implemented in recent decades were effective and China may enter the low-carbon industrialization process.

Third, CO_2 intensity was diversified across provinces and the diversification was relatively greater in the periods of 1995-2002 and 2003-2007 than in the period of 2008-2010. Taking the phase of 1998-2002 as an example, we can see that provinces like Sichuan, Hainan, Fujian, Guangdong,

[4] The official U.S Dollar to RMB (China's official currency) exchange rate is about 6 *yuan* in 2012.

Zhejiang, and Guangxi have relatively lower CO_2 intensities, while provinces like Yunnan, Heilongjiang, Jilin, Liaoning, Inner Mongolia, and Gansu have relatively higher CO_2 intensities. Other provinces, like Jiangsu, Shanghai, Beijing, Jiangxi, Hunan, Shandong, Henan, Hubei, Anhui, Tianjin, Chongqing, Shanxi, Xinjiang, Ningxia, and Hebei, have middle-level CO_2 intensities.

Fourth, CO_2 intensity was spatially agglomerated. It can be seen that the differences in CO_2 intensity across the eastern provinces were shrinking, indicating a pattern of agglomeration of low energy-intensive industries there. There being far more highly energy-intensive industries agglomerated in the middle/western regions than in the eastern region, thus the middle/western regions have a much higher level of CO_2 intensity than the eastern region.

Last, although the differences in CO_2 intensities across the western provinces were still large in general, the CO_2 intensity in some western provinces, which are geographically close to the eastern areas, has been approaching that of nearby eastern provinces, while this trend was not apparent in the western provinces that are far away from the eastern provinces. This finding confirms our hypothesis of spatial dependence.

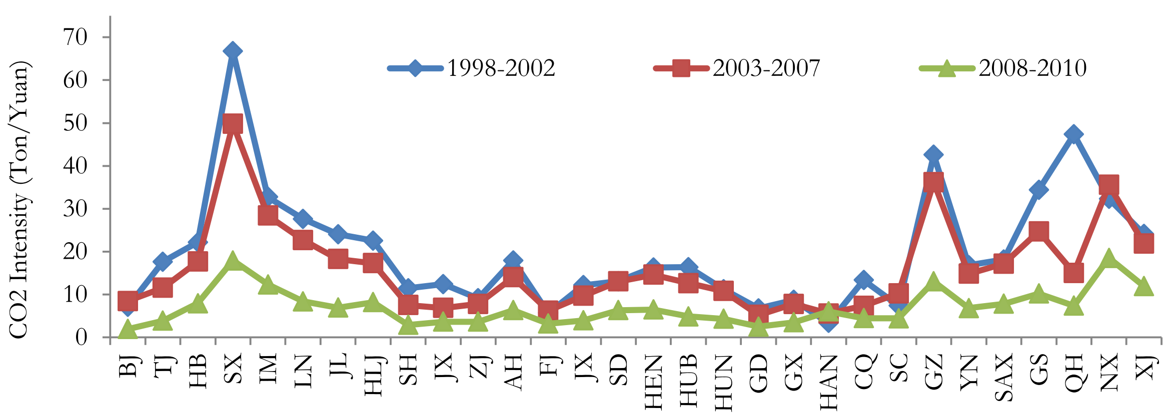

Fig. 2 The provincial distribution of CO_2 intensity between 1998 and 2010

Note: BJ = Beijing; TJ=Tianjin; HB =Hebei; SX = Shanxi; IM = Inner Mongolia; LN = Liaoning; JL = Jilin; HLJ = Heilongjiang; SH = Shanghai; JX = Jiangxi; ZJ = Zhejiang; AH = Anhui; FJ = Fujian; JX = Jiangxi; SD = Shandong; HEN = Henan; HUB = Hubei; HUN = Hunan; GD = Guangdong; GX = Guangxi; HAN =Hainan; CQ = Chongqing; SC = Sichuan; GZ = Guizhou; YN = Yunnan; SAX = Shaanxi; GS = Gansu; QH = Qinghai; NX = Ningxia; XJ = Xinjiang.

3 Model Specification

This study uses the dynamic spatial panel data model, which differs from the traditional panel data model by taking into account both dynamic and spatial effects of provincial CO_2 intensity. This model has become popular in the last decade since it combines time series econometrics, spatial econometrics, and panel econometrics. Elhorst (2012) points out that methods developed either for dynamic but non-spatial or for spatial but non-dynamic panel data models all produced biased estimates.

The dynamic spatial lag panel data model is traditionally specified as follows (Elhorst, 2010; Lee and Yu, 2010; Zheng et al., 2013),

$$y_{it} = a + \theta y_{i,t-1} + \varrho \sum_{j=1} W y_{jt} + \sum_k x_{it}^{(k)} \beta_k + \mu_i + \upsilon_t + \varepsilon_{it},\ i = 1,\ldots, N;\ t = 1,\ldots,T \quad (3)$$

where y_{it} is the dependent variable representing CO_2 emissions intensity in province i at time t. W is a non-stochastic, predetermined, contiguity-based binary matrix in which each element w_{ij} is set to be one if provinces i and j ($i \neq j$) share a common border, and zero otherwise. In addition, the matrix W is commonly row-standardized such that the elements of each row sum to one. x_{it} is a $k \times 1$ vector of independent variables. θ reflects the dynamic effects of CO_2 intensity. ϱ is the main concern of this study and represents the spatial lag parameter that characterizes the strength of contemporaneous spatial correlation between one province and other geographically proximate provinces. μ_i is the provincial fixed effect, υ_t is the fixed temporal effect, and ε_{it} is the idiosyncratic disturbance term assumed to be standard normal, independent of each other and everything else. When $\varrho = 0$, Equation (3) reduces to the traditional dynamic panel setting, while $\theta = 0$ will reduce the model to the static spatial econometric model.

In terms of econometric estimation, the most parsimonious panel model, or the static panel data model which has neither dynamic effects nor spatial effects, can be estimated by the least-squares dummy variables (LSDV) estimator if the spatial-specific effects can be considered as fixed effects, or by the generalized lest-squares (GLS) estimator if the spatial-specific effects can be considered as random effects (Hsiao 2003; Baltagi 2008). Extension of the static panel data model with a dependent variable lagged in time (Y_{t-1}) formulates a dynamic panel data model. The LSDV and GLS estimators to estimate the dynamic panel data model become inconsistent if T is fixed, regardless of the size of N (Arellano 2003; Baltagi 2008), which is because the lagged dependent term Y_{t-1} is correlated with the spatial-specific effect.

The most popular approach to remove this inconsistency is generalized method of moments (GMM). By creating a set of estimating equations for the parameters by making sample moments match the population moments, one derives the estimators from the moment conditions, and also a set exogenous variables (i.e., correlated with Y_{t-1} but uncorrelated with the errors) that can be used to instrument Y_{t-1}. The Anderson-Hsiao (1982) or Arellano and Bond (1991) difference GMM rests on the idea that using first differencing to eliminate the unobserved spatial effects, and then lags two and beyond (Y_1, …, Y_{t-2}, $t \geq 3$) are used as instrumental variables for the differenced lagged dependent variable (ΔY_{t-1}). While the difference GMM approach can correct for the dynamic panel bias or Nickell's bias (1981) caused by the least squares regression that includes spatial-specific effects or the least squares dummy variable (LSDV) model, it may suffer from finite sample bias and precision problems when the data series are persistent or are close to a random walk (Blundell and Bond, 1998), as the instruments (i.e., Y_1, …, Y_{t-2}) are weak predictors of the endogenous changes (i.e., ΔY_{t-1}).

To overcome the drawbacks of the difference GMM approach, a closely related but improved GMM dynamic panel approach, named system GMM, was proposed by Arellano and Bover (1995) and later developed by Blundell and Bond (1998), which uses extra moment conditions that rely on certain stationarity conditions of the initial observation. In other words, the system GMM approach also uses lagged first differences for the equation in levels (i.e., the system GMM estimator also instrument Y_{t-1} by the variables $\Delta Y_1,\ldots, \Delta Y_{t-2}, \Delta X_1,\ldots, \Delta X_{t-1}$). Blundell and Bond (1998) argue that the system GMM estimator performs better than the difference GMM estimator because of the following properties: 1) increased efficiency; 2) less finite sample bias; 3) the instruments used in the level equation model remain good predictors for the endogenous variables even when the series are very persistent. Because of the good performance of the system GMM estimator compared with the difference GMM estimator, it has become more popularly used in the panel data settings.

Ten years after the paper of Blundell and Bond (1998), several studies such as Kukenova and Monteiro (2009) and Jacobs et al. (2009) extended the system GMM estimator of Blundell and Bond (1998) to account for the spatial effects. The spatial system GMM is known to have the advantage on avoiding the bias problem (especially with respect to the spatial autoregressive parameter, ϱ) from the spatial difference GMM estimator (Kukenova and Monteiro, 2009; Jacobs et al., 2009; Elhorst, 2010), and over traditional spatial maximum likelihood estimation (MLE) in that the system GMM estimators can also be used to instrument endogenous explanatory variables (other than Y_{t-1} and WY_t). For this reason, we will use the latter approach in this empirical study.

A few remarks are needed to better understand the spatial system-GMM estimator. First, the number of sample observations is relatively large and the time span of interest is relatively short, as a long time span would easily cause the over-identification problem of instrumental variables. The sample in this study covers 30 provincial units from 1998 to 2010, so the first prerequisite could be satisfied.[5]

[5] It should be mentioned that dynamic panel is designed for micro-level panel data large N and small T. The available sample we have has only $N = 30$, which may be worrisome.

Second, the consistency of the system GMM estimator (and difference GMM estimator as well) rests on the assumption that there is no first-order serial autocorrelation (i.e., AR(1) $\neq$ 0) in the error terms of the level equation, or equivalently, there is no second-order serial autocorrelation (i.e., AR(2) = 0) in the first-differenced errors. The Arellano and Bond (1991) test is used in this empirical work. If the above assumption is violated, the instrumental variables can be highly correlated to the endogenous variables and the model might not be specified correctly. One way to tackle this issue is to add dependent variables of more than one lag in the model.

Third, the instrumental variables have to be relevant and valid, which implies that the following two requirements have to be satisfied: 1) instrument relevance, under which the chosen instruments have to be highly correlated with the endogenous regressors even after controlling for the exogenous regressors. This requirement can be empirically tested in the first stage regression using a joint F test of whether all excluded instruments are statistically significant, and 2) instrument exogeneity, which can be tested using the Sargan (1958) or Hansen (1982) over-identification test in case there are more excluded instruments than the number of endogenous variables.

Fourth, before implementing the spatial dynamic Blundell–Bond-type system-GMM regression, it is necessary to test for the spatial interaction effects. In a cross-sectional setting, Anselin et al. (1996) developed two Lagrange multiplier (LM) tests for spatially lagged dependent variables and for spatial error correlation, and two robust counterparts of these two LM tests. For panel data setup, the first two LM tests are: LM-LAG = $[e'(I_T \otimes W)Y/\hat{\sigma}^2]^2/J$, and LM-ERROR = $[e'(I_T \otimes W)e/\hat{\sigma}^2]^2/(TT_W)$, where the symbol $\otimes$ denotes the Kronecker product, I denotes the identity matrix, T is the order of the matrix, and e denotes the estimated residual from the non-spatial dynamic panel model. J and T_W are defined as follows: $J = [((I_T \otimes W)X\hat{\beta})'(I_{NT} - X(X'X)^{-1}X')(I_T \otimes W)X\hat{\beta} + TT_W\hat{\sigma}^2]/\hat{\sigma}^2$, and T_W = trace$(WW + W'W)$. The two robust LM tests are defined as follows: Robust LM-LAG = $[e'(I_T \otimes W)Y/\hat{\sigma}^2 - e'(I_T \otimes W)e/\hat{\sigma}^2]^2/(J - TT_W)$, and Robust LM-ERROR = $[e'(I_T \otimes W)e/\hat{\sigma}^2 - TT_W/J \times e'(I_T \otimes W)Y/\hat{\sigma}^2]^2/[TT_W(1 - TT_W/J)]$. Detailed derivations of these tests for a spatial panel data model with spatial fixed effects can be found in Debarsy and Ertur (2010). Under the null hypothesis, these tests follow a chi-squared distribution with one degree of freedom.

4 Data Source

We used a panel data set of 30 provincial units (22 provinces, 4 municipalities, and 4 autonomous regions) from 1998 to 2010.[6] The dependent variable is the CO_2 intensity, which is defined as the provincial CO_2 emissions divided by provincial GDP. Data on the provincial CO_2 emissions during the sample period are available from the Energy Economic Center at Renmin University of China (http://rucee.ruc.edu.cn), where the CO_2 emissions are calculated based on the method offered by the Intergovernmental Panel on Climate Change (IPCC), and on other information, such as total consumption of various energies, the heat content, the carbon content, and the carbon oxidation rate of each energy, and so on.

The potential independent variables are identified as follows. *GDP* is an important factor that affects CO_2 intensity. Some empirical studies found that there exists a non-linear relationship between GDP and the CO_2 intensity. For instance, Roberts and Grimes (1997) found that the CO_2 intensity and per-capita GDP have an inverted *U*-shaped relationship, which indicates that CO_2 intensity would fall eventually as the economy develops even without any external reduction policies. Other studies also found that the relationship can be *N*-shaped (Moomaw and Unruh, 1997; Friedl and Getzner; 2003; Millimet et al., 2003; Galeotti and Lanza, 2005; Yu et al., 2011). *POP*, indicating population size, is another important factor that affects CO_2 intensity. The larger the population size, the more direct and indirect is energy consumption, and the greater the CO_2 emissions. Historical data show that the population and CO_2 intensity are positively related. *FDI* measures foreign direct investment. The relation between FDI and the CO_2 intensity is ambiguous. On the one side, inward FDI takes into account not only capitals but also advanced technologies, equipment, and management experience invested in China. These investments help to improve the efficiency of energy consumption and reduce pollution. Hence, FDI, to some extent, contributes to the decline of CO_2 intensity in China. On the other hand, the rise in exports due to FDI leads to the growth in implicit energy consumption and hence CO_2 emissions. Moreover, a large amount of FDI went into pollution-intensive industries, which would result in an increase in CO_2 intensity. Therefore, the relationship between FDI and CO_2 intensity is not clear and deserves further empirical analysis.

SEC is measured as the ratio of value-added from the secondary industries to the total industry value-added. Currently, the ratio of the primary, secondary, and tertiary industries in China is 1:5:4 (Yu et al., 2011) and the growth in the economy is heavily dependent on the secondary industries, especially on the industries with high-energy consumption and high pollution. The CO_2 emissions of

[6] Tibet is excluded from the sample because of the lack of data.

the secondary industries are much more than those of the primary and tertiary industries. Therefore, we expect the coefficient of this variable to be negative. *RD* is defined as the ratio of research and development (R&D) expenditure to GDP. R&D inputs can affect CO_2 intensity in two respects. On the one side, based on the endogenous growth theory, the advancement of technology (say, low-carbon technology) improves the utilization of natural resources, so the resources could be saved and recycled. From this point of view, science and technology innovation has a positive effect on the reduction in CO_2 intensity. On the other side, R&D expenditure might increase CO_2 emissions because the main concern of science and technology innovation is to increase output rather than to reduce CO_2 emissions. Therefore, the relationship between R&D and CO_2 intensity is also ambiguous.[7]

The data on the aforementioned variables, including *GDP*, *POP*, and *SEC*, are obtained from the *China Statistical Yearbook* which is compiled by China Statistical Press. The *FDI* data come from the CEIC Database.[8] The R&D expenditure data are taken from *China Statistical Yearbook on Science and Technology*. The variables used in the empirical model and their summary statistics are presented in Table 1.

Table 1 Description and Statistics of Variables

	Mean	Std Dev
Dependent variable		
INTENSITY	33,087.320	25,966.710
Independent variable		
GDP	1.975	2.428
GDP2	9.781	43.735
GDP3	112.245	978.586
SEC	46.409	7.422
POP	4,206.466	2,651.257
RD	0.010	0.009
FDI	2,883.916	4,509.359

Note: INTENSITY: CO_2 emission intensity (tons/100 million *yuan*)
GDP: per capita GDP (10 thousand *yuan*/person)
GDP2: GDP squared
GDP3: GDP cubed
SEC: ratio of value-added from the secondary industry to total industry value-added (%)
POP: population size (10 thousand persons)

[7] It is worth mentioning though that R&D's scale is rather small compared with the product process, which implies that even though R&D has positive or negative effect on carbon intensity, the effect may be true only in terms of statistical significance instead of economic significance.

[8] CEIC is an euromoney institutional investor company (http://www.ceicdata.com/). CEIC Data provides the most expansive and accurate data insights into both developed and developing economics around the world.

RD: ratio of R&D expenditure to GDP (%)
FDI: foreign direct investment (US $)

5 Empirical Findings

The base empirical results are shown in Table 2. Beginning with the static panel regressions in Table 2,[9] the Hausman test statistics (21.38, p = 0.000) indicates that fixed effects model (FEM) is preferred to the random effects model. The coefficient regression results show that the coefficients of *GDP*, GDP squared (*GDP2*), and GDP cubed (*GDP3*) are, respectively, negative, positive, and negative. Besides, all estimates are statistically significant at the level of 1%. This result suggests that CO_2 emission intensity and GDP are nonlinearly related, which is expected. Specifically, they have an inverted *N*-shaped relationship rather than an inverted *U*-shaped relationship or a linear relationship. Yet, population size and R&D are found to have neither positive nor negative effects on CO_2 emission intensity. Besides, a higher share of the secondary industry is negatively associated with CO_2 emission intensity. Certainly, this conflicts with theory. This is because the FEM model does not take into account the endogeneity and dynamic attributes of the data.

Turning attention to the dynamic panel model (i.e., the system-GMM model) in Table 2, the system GMM model accounts for endogeneity, but ignores spatial interactions across jurisdictional CO_2 emission intensities. The system GMM results are generally more plausible than those from FEM, as evidenced by diagnostic tests for autocorrelation and Hansen test for over-identification. Furthermore, the lagged parameter of CO_2 emission intensity is positive and statistically significant, suggesting evidence of dynamic nature of CO_2 emission. GDP terms now have smaller (in absolute value) relationship with CO_2 emission intensity than was suggested by the FEM estimates. In addition, share of the secondary industry is positively associated with emission intensity, R&D is negatively related to emission intensity. These results are expected, while the negative and statistically significant coefficient estimate for population size seems unexpected. Yet, like the FEM model, the system-GMM model has problems of model specification. Particularly, the system-GMM estimates suffer from omitted variable bias due to ignorance of spatial spillovers effect (or spatially lagged dependent variable), as evidenced by Moran's *I* and robust LM tests for spatial autocorrelation (Table 2).

[9] We conducted the panel unit root tests (Levin, Lin and Chu (LLC, 2002), Im Pesaran and Shin (IPS, 2003), and Phillips and Perron (PP, 1988)) for the explanatory variables in this study. We found in general that *GDP* and *FDI* are *I*(1) processes, while *SEC* and *RD* are I(0) processes. So eventually we assumed all variables are generated by a stationary process in time given these mixed results and to avoid complications.

The last column of Table 2 shows the fully-specified spatial system-GMM results.[10] The error term's first-order serial correlation test, second-order serial correlation test, and Hansen over-identification test indicate that the system-GMM does not have the misspecification problem and that the instrumental variables selected are indeed exogenous.[11] The coefficient estimates for the CO_2 emission intensity equation now reflect some major changes from non-spatial system-GMM and some main results are summarized as follows.

First, the spatial lagged coefficient ϱ is positive and statistically significant at the 1% level, which indicates that the CO_2 intensities in the neighbouring provinces have a positive impact on one's own province's CO_2 intensity. Specifically, as the CO_2 intensity in the neighbouring provinces rises on (spatial) average by 1%, *ceteris paribus*, the CO_2 intensity in the province of interest would rise by 0.03%.

Second, the inverted N-shaped relationship remains valid between CO_2 intensity and GDP. Such finding is not in line with the EKC literature, but is consistent with Moomaw and Unruh (1997), Du et al. (2007), and Yu et al. (2011). Yet, a noteworthy change from the non-spatial model (FEM, or system GMM) to the spatial system-GMM model is that GDP terms now have smaller (in absolute value) relationships with CO_2 emission intensity than was suggested by the FEM or system GMM estimates.

Third, like the system-GMM estimate, a higher share of the secondary industry is positively associated with CO_2 emission intensity. This finding is predicted by theory as China's economy is heavily dependent on secondary industries, such as steel and iron, aluminium smelting, cement, chemicals, and transportation industries, and these industries are also the ones that emit the most CO_2.

Fourth, R&D remains to be statistically insignificant at the 10% level, implying that technological innovation has no obvious effect on provincial CO_2 intensities. This result is beyond our expectation. The potential reasons can be three-fold: first, all levels of government are the leading forces of R&D investment in China, some so-called 'science and technology achievements' fail to be converted into production; second, the ratio of R&D expenditure to GDP may not be a good measurement of technological innovations; and third, in the extensive economic growth stage, R&D expenditure in China increased the CO_2 emissions because the main concern of science and technology innovation

[10] Analyses are done using STATA 12.0, a data analysis and statistical software, and some of the STATA modules to implement the diagnostic tests and spatial regressions are made by Emad Shehata (http://emadstat.110mb.com/stata.htm).

[11] Economic theory rarely gives us information about the lag length (Y_{t-1}, Y_{t-2}), which is usually determined empirically. Since our diagnostic test statistics indicate we pass all the tests, specification of a lag = 1 is sufficient to give us consistent estimators. Indeed, the likelihood-ratio test result (not shown) shows that the likelihood value of the model specification with lag = 1 is slightly larger than that with lag = 2, which again confirms our choice of lag length.

is to increase output rather than to reduce CO_2 emissions. Hence, these factors combined make the overall effect of R&D on provincial CO_2 intensities insignificant.

Fourth, population size remains to be negative and statistically significant at 1% level. The negative effect of population size, which seems puzzling at a first glance since it is usually believed that more population leads to more energy consumption direct or indirectly and hence more CO2 emission (intensity), could imply that population size is associated with some agglomeration force that could improve the production efficiency which leads to a reduction in emission intensity of carbon dioxide. However, another noteworthy change is that the coefficient on population size from the spatial system-GMM estimation decreases by almost three fold (from −3.54 to −1.28), suggesting that system GMM without accounting for spatial dependence overestimates the population effect.

Last, most notably, FDI is now inversely related to CO_2 intensity. As mentioned, the effect of FDI on CO_2 intensity is theoretically ambiguous, as, on the one side, FDI may reduce local CO_2 intensity by introducing advanced technologies which help to improve the efficiency of energy consumption; whereas, on the other side, FDI transfers some overseas high energy consumption industries to China, which increases the overall consumption of energy and raises CO_2 intensity. The empirical findings show that the latter effect of FDI on CO_2 intensity dominates the former. This result is consistent with Yu (2012).

The striking changes from the FEM and system-GMM to the spatial system-GMM model point to the adequacy of accounting for dynamic factor, endogeneity, spatial autocorrelation, and spatial heterogeneity jointly.

Table 2 Determinants of Provincial CO_2Emissions Intensity in China

	Static panel model (fixed-effects model)	Dynamic panel model (system-GMM)	Spatial dynamic panel model (spatial system-GMM)
θ (dynamic factor)		0.613^{***}	0.432^{***}
		(10.35)	(5.07)
ϱ (spatial factor)			0.034^{***}
			(12.10)
GDP	-111.653^{***}	-49.501^{***}	-93.092^{***}
	(4.67)	(4.92)	(12.95)
GDP2	947.861^{***}	617.861^{***}	99.587^{***}
	(3.74)	(3.25)	(8.51)
GDP3	-22.687^{***}	-18.749^{**}	-9.622^{***}
	(3.06)	(2.38)	(6.13)
SEC	-499.476^{**}	116.834^{**}	130.842^{***}
	(2.04)	(2.32)	(4.51)

POP	−2.439	−3.543**	−1.283***
	(0.97)	(2.03)	(6.71)
RD	−141,487.115	172,590.853	−38,387.180
	(0.33)	(0.73)	(0.62)
FDI	0.804*	1.009	0.226*
	(1.85)	(1.57)	(1.78)
Constant	80,965.100***	29,313.953***	17,234.700***
	(5.58)	(3.05)	(10.76)
Province dummy	Y	Y	Y
R squares	0.341		
Obs.	390	390	390
No. of provinces	30	30	30
Hausman test of fixed vs. random	21.38 [0.000]		8.97 [0.000]
Spatial Panel Autoregression Test			
LM-Error Panel Test			[0.111]
Robust LM-Error Panel Test			[0.125]
LM-Lag Panel Test			[0.023]
Robust LM-Lag Panel Test			[0.057]
System GMM Test			
AR(1) Test		[0.007]	[0.068]
AR(2) Test		[0.403]	[0.279]
Hansen Over-identification Test		[0.998]	[0.999]

Note: (i) ***, **, and * stand for the statistical significance at the level of 1%, 5%, and 10%, respectively; (ii) absolute *t*-values are in parentheses; (iii) *p*-values are in square brackets; (iii) spatial fixed or random effects are compared using Hausman's specification test that is developed by Lee and Yu (2010).

6 Conclusions

Using a panel data set of 30 provincial units from 1998 to 2010, this study examined the determinants and spatial nexus of the provincial CO_2 intensities in China by estimating a spatial dynamic panel (system-GMM) model. The dynamic factor, spatial dependence, and spatial heterogeneity of the provincial CO_2 intensities are rarely examined together in the existing literature. In this paper, we found that provincial CO_2 intensities are spatially dependent, CO_2 intensity is increasing from the eastern regions to the western regions, and the spatial agglomeration effects are obvious. In particular, we found that CO_2 intensities are spatially correlated across provinces, and the correlation tends to increase over time. The Moran's scatterplot shows that most provinces appeared in the first (HH) and the third (LL) quadrants, which also reveals the spatial dependence, as it can be seen that provinces in the same quadrant are the ones that are geographically proximate to each other (e.g., provinces in the

Yangtze River Delta region, provinces in the Pearl River Delta region, and Gansu, Ningxia, Inner Mongolia, and Xinjiang provinces).

China's CO_2 intensity target that reducing the carbon emission by 40-45% in 2020 compared to 2005 is a big step in the right direction and it provides the right incentives for future improvements in reducing emissions. Several policy suggestions on reducing CO_2 intensity can be drawn based on our empirical results. First, imposing a pollutant tax. Although energy or carbon tax is suggested by numerous literatures, it can be a two-edged sword. On one hand, it contributes to reducing the demand of coal and other energies that helps to cut down the CO_2 emissions. On the other hand, it has negative impact on energy-intensive industries as well as the macro-economy. Wei and Glomsrod (2002) pointed out that if the government levy USD5 per ton of carbon as tax, the CO_2 emission would be reduced by 0.21 billion; meanwhile, the GDP would drop by 29 billion Chinese *yuan* in 2020. In other words, the cost of reducing one ton of carbon emission is about 496 Chinese *yuan* (USD82.67) which is much higher than USD5's tax. Our finding of inverted *N*-shaped relationship between CO2 intensity and GDP shows that the environment can actually benefit from the growth of GDP. Thus, it is preferable to levy tax based on pollutant directly, which is more efficient and relatively less harmful to the economy. Also, we consider a progressive tax rate increment with a low initial tax rate will mitigate the negative effects of tax on the economy. Furthermore, to compensate for the loss in GDP resulted from pollutant tax, we suggest the central and local governments recycle the tax revenue by cutting down energy-intensive industry's production tax. In this case, pollutant tax brings a "double dividend" (improvement both in environment and economic efficiency).

Second, the spatial dependence found within in study implies that transboundary pollution associated with CO_2 emissions is potentially a real issue. This regional pollution problem is further complicated by the fact that the coal consumed in some provinces is imported from other provinces. The regional plans to reduce emissions then must inevitably involve energy trading. It is possible that neighbouring provinces may develop cooperative initiatives to reduce emissions. Taking the CO_2 emission quota as an example, central government should allocate the quota across provinces based on the provincial factor endowments and allow for quota transactions among provinces. The western/middle provinces have relatively larger CO_2 emissions because most of the energy-intensive industries are located there, so those provinces should have more of the quotas. Local governments should make good use of their comparative advantages to improve energy utilization, which can not only lower the local CO_2 intensity, but also achieve extra benefits by selling unused quotas.

Third, optimizing the industrial composition by enhancing the development of green industries and constraining the development of high-carbon consumption industries. Meanwhile, positively developing the environmental friendly alternative energy sources, such as solar energy, wind energy, and hydro energy.

Fourth, enlarging the R&D investment aiming at recycling CO_2 emissions besides improving energy efficiency and reducing CO_2 emission. We suggest governments of all levels earmark the pollutant tax revenue as the R&D fund that is used exclusively for CO_2 emission recycling and reduction. We also recommend that governments should facilitate the cooperation between energy-intensive industry and local universities as well as other research agencies to make a fully use of their comparative advantage in research. Besides, governments should set up a supervision division to guarantee the transfer of the research achievements into productivity.

Last but not least, fostering enterprises' low-carbon production and creation consciousness. Using proper policies to guide the enterprises to make correct choice between the low-carbon technique and traditional business, as well as between the short-run profits and long-run development. Moreover, encouraging the citizens to engage in energy-saving and emission-reduction activities and constructing an intensive, economical, and ecological development trajectory. The bottom line is that these policies, regulations or initiatives need to start being developed soon. Nonetheless, China's carbon intensity target still leaves room for even more ambitious action.

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