Journal of Applied Science and Engineering Innovation, Vol.10, No.2, 2023, pp. 113-119
ISSN (Print): 2331-9062
ISSN (Online): 2331-9070

# Do financial development and industrial structure upgrading affect carbon emissions in China since the recent financial crisis? An empirical investigation

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**Abstract:** Both financial development and industrial structure may have great effects on an economy and hence on carbon emissions. However, no research has examined the effect of these two variables on carbon emissions in China against this background to date. To fill up this gap, a Spatial Durbin Model is used to investigate the effects of financial development and industrial structure upgrading on carbon intensities in China from 2007 to 2017. The results show that financial development increases local carbon intensities but decreases adjacent areas' carbon intensities to a larger extent, so that it has an overall negative effect on carbon emissions. This suggest that financial resources in China were not channeled into environment-protecting projects. Further, industrial structure upgrading has no significant effects on carbon emissions. The paper suggests that China should direct its financial resources into energy saving, emission reduction and industrial structure upgrading projects and firms to achieve a "both good and fast" growth as it wishes.

**Keywords** Wealth accumulation regime; Post-Fordism regime; Finance; Spatial Durbin model

## INTRODUCTION

The Chinese government has made great efforts to tackle the climate problem and great achievements has been realized. However, still greater efforts need to be made to further achieve it later objectives of emission reduction.

Chinese government has rigorously pushed the upgrading of its industrial structure to save energy and reduce emissions since then to reach this goal. The second reason that the year 2007 is special is that the global financial crisis started in 2007 affected China significantly.i,ii To illustrate, the annual GDP growth declined from more than 14% in 2007 to 6% in 2017. The Chinese government introduced a large economic stimulus plan in 2008 to recover, including the domestic Four Trillion Yuan Stimulus Package. As a result, Chinese financial industry started to grow rapidly: the ratio of the GDP of the financial industry increased from 4.57% in 2007 to 8.01% in 2017, accompanied by a increase of the ratio of employment by the financial industry of 0.517% in 2007 to 0.887% in 2017. Meanwhile, financial resources boomed. To illustrate, total credit increased by 4.25 times, from 45426.78 billion RMB in 2007 to 193193.4 billion in 2017; M2 increased by 4.57 times, from 25088.2 billion in 2007 to 114644.52 billion in 2017. China's carbon intensity decreased greatly from 2007 to 2017, while financial development (measured by the ratio of financial institutions' loans to GDP) increased obviously and steadily. Though industrial upgrading (measured by the ratio of second and tertiary GDP) also improved, its improvement was no as evident compared with the trend of carbon intensity and financial development during this period. These changes in the industrial structure and financial development will certainly affect the carbon emissions of the economy.

No research has examined the effect of these two variables on carbon emissions in China against this background up to now. This study specifically investigates the effect of financial development and industrial structure upgrading on carbon emissions since the 2007.

The rest of the paper is organized as follows. Section two is a brief literature review. Section three is the theoretical mechanism that FD and industrial structure upgrading may affect carbon emissions. The methods and data used are described in section four. Section five presents the results and discussions. The final section concludes and discusses related policy implications.

## METHODOLOGY AND DATA

### Measuring provincial carbon intensity

Carbon intensity is measured as the ratio of $CO_2$ emissions to GDP as shown in Eq. (1)

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$$CI=CE/GDP \quad (1)$$

where CI is the carbon intensity of a province, and CE is the CO2 emissions of that province. The CO2 emissions in the paper are calculated using the method recommended in the Intergovernmental Panel on Climate Change's "Guidelines for National Greenhouse Gas Inventories". The calculation method is shown in Eq. (2).

$$CE = \sum_{k=1}^{9} CE_k = \sum_{k=1}^{9} E_k \times SC_k \times LCV_k \times CEC_k \times COF_k \quad (2)$$

Nine major energy sources are selected to measure the CO2 emissions, which include raw coal, cleaned coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas; k represents the type of energy (k = 1,2,...,9). In order to avoid missing the calculation of CO2 emissions in the process of energy conversion, E is the amount of energy available for local consumption. SC represents conversion coefficient of standard coal, LCV represents the average low-order calorific value, and CEC represents the carbon emission coefficient and COF represents the carbon oxidation rate. It is assumed that carbon in the fuel is completely oxidized during combustion in this paper. Hence, COF is equal to 100%.

The data cover annual data of China's 30 provinces (excluding Hong Kong, Tibet, Macao, and Taiwan for lack of data) from 2007 to 2017. All the energy related data were compiled from China Energy Statistical Yearbook, while GDP were from China.

### Measuring spatial auto-correlation of provincial carbon intensity

The CO2 emissions of a region may be spatially dependent on those of neighboring regions. Moran's I is applied to identify the pattern of global auto-correlation of China's provincial carbon intensities. Generally, Moran's I is between -1 and 1. When Moran's I > 0, it indicates positive spatial correlation; the larger the index value, the more obvious the spatial aggregation. When Moran's I <0, it indicates negative spatial correlation; the larger the index value, the greater the spatial difference. Otherwise, Moran's I = 0, which means a random distribution of space.

$$I = \frac{n}{S_0} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(X_i - \overline{X})(X_j - \overline{X})}{\sum_{i=1}^{n}(X_i - \overline{X})^2} \quad (3)$$

Where: n —the number of provinces, n = 30; $X_i$ — the carbon intensity of province i; $X_j$ — the carbon intensity of province j; $\bar{X}$ — the average carbon intensity of each province; $w_{ij}$ — the spatial weight matrix, here the weight is the reciprocal of the squared geographical distance between two provinces' capital cities; $S_0$ — the sum of all spatial weights.

Generally, the z score, usually the difference of a value and its mean divided by its standard deviation, can test the significance of Global Moran's I.

### Data and variables

The dependent variable is carbon intensity. The two main independent variables are financial development and economic structure upgrading (or industrial structure upgrading). Industrial structure upgrading is proxied by the radio of GDP of the secondary industry plus tertiary industry to provincial GDP. The ratio of financial institutions' loans to GDP is used to measure the main independent variable, FD, as many scholars use the same measure as ours to measure financial development, and this measure is particularly appropriate in China since loans are a primary means of financing and affect the activities of firms greatly, since the capital market there is not as developed and rational yet. 22

The control variables are selected according to environmental impact models— IPAT (put forward by Ehrlich in 1971) and STIRPAT model,iii with the latter being an extended form of the former. Equation (5) is the general STIRPAT model.

$$I = aP^b A^c T^d e \quad (5)$$

where I represents environmental pressure; P, A and T represent population, affluence and technology, respectively; a is a constant term; b, c, and d are exponential terms of P, A, and T, respectively; e is an error term. Hence, control variables that affect carbon intensity are chosen from three aspects: population, affluence and technology.

Urbanization is used to represent population factor, GDP per capita is used to represent economic growth, and patent applications and FDI to proxy domestic technology and foreign technology, respectively. Further, as energy intensity may proxy energy-saving and emission-reduction technologies, it is also controlled in our model (Zhao et al错误!未定义书签。; Liu et al., 2017iv; Liu et al., 2016v). The GDP and FDI data are deflated by the 2005 price level. Table 1 shows the specific meaning and details of the variables. The financial development data were collected from EPS, patent applications from China Science and Technology Statistical Yearbook, and the rest as mentioned in section 4.1.

Introducing our main and controlled variables into equation (5) and transforming it into the logarithm form to eliminate heterogeneity, we have the following panel regression model, before considering the spatial effects of variables:

$$\ln CI = \beta_0 + \beta_1 \ln FD + \beta_2 \ln ISU + \beta_3 \ln UR + \beta_4 \ln PGDP + \beta_5 \ln T + \beta_6 \ln FDI + \beta_7 \ln EI + \varepsilon \quad (6)$$

where $\beta_0$ is the intercept, $\beta_n$ (n=1, 2,……,7) is the coefficients of the independent variables, and ε is the random error.

Table 1. Variable definitions and descriptions

| Variables | Definitions |
|---|---|
| PCO2 | Per capita carbon dioxide (CO2) emissions |
| FI | Financial inclusion composite index |
| PGDP | Economic growth measured by the real per capita GDP, which applies 2005 as the base period |
| IS | Industrial structure upgrading computed by the proportion of the output value of tertiary industry to that of secondary industry |
| UL | Urbanization evolution evaluated by the ratio of urban population to total population |
| P | Regional population |
| EC | Energy intensity is measured by the amount of energy consumed per unit of GDP |

In order to examine whether there are severe multicollinearity in the seven independence variables, Variance Inflation Factor (VIF) test are conducted according to the equation (5).The VIF of the variable urbanization is greater than ten. Hence, there is serious multicollinearity in the model of the seven independence variables. Then the method of omitting variable is used to eliminate multicollinearityvi and we omitted the variable urbanization. Ultimately, the VIF test results of 6 explanatory variables shows that the VIF of all variables are less than ten, indicating no serious multicollinearity in the six variables. Therefore, the independence variables are finally determined to be financial development, industrial structure upgrading, GDP per capita, technology, FDI and energy intensity in the model.

**The spatial econometric model**

The CO2 emissions of a region may be spatially dependent on those of neighboring regions. Moran's I is applied to identify the pattern of global auto-correlation of China's provincial carbon intensities. Generally, Moran's I is between -1 and 1. When Moran's I > 0, it indicates positive spatial correlation; the larger the index value, the more obvious the spatial aggregation. When Moran's I <0, it indicates negative spatial correlation; the larger the index value, the greater the spatial difference. Otherwise, Moran's I = 0, which means a random distribution of space.

As is proved by many, China's carbon emissions have significant spatial dependence and inaccurate results will be derived using econometric models without consideration of the spatial dependence of variables.3,4 Hence, spatial econometric models will be applied to investigating the effect of financial development and industrial upgrading on carbon emissions in China in this paper. Currently, there are three models commonly used in spatial panel data regression: spatial lag models (SLM), spatial error models (SEM) and spatial Durbin models (SDM). The spatial lag variable of the dependent variable is introduced into Spatial lag models as an explanatory variable, the spatial lag variable of the standard error is introduced into the spatial error models (SEM) as one explanatory variable, while both are introduced into the spatial regression model to be the spatial Durbin model. Hence, spatial Durbin models, which could be expressed as equation (7), are in fact a general form of SEM and SLM, and could be reduced to SLM or SEM under certain conditions.

$$D_{it} = \delta W D_{it} + X_{it}\beta + W X_{it}\theta + v_i + \gamma_t + \varepsilon_{it} \qquad (7)$$

Where: $D_{it}$ —the dependent variable; W —the geographical distance spatial weight matrix; $\delta$ — the coefficient of the spatial lag term of the dependent variable; $X_{it}$ —the vector of explanatory variable; $\beta$ — the coefficient of the independent variables; $\theta$ — the coefficient of the spatial lag term of the independent variable respectively; $v_i$ and $\gamma_t$ —the intercepts of the spatial effect model and time effect model respectively; $\varepsilon_{it}$ — the random error.

According to equation (7), the following SDM is employed to investigate the effect of financial development and industrial structure upgrading on carbon emissions:

$$ln\,CI = \beta_0 + \beta_1\, ln\,FD + \beta_2\, ln\,T + \beta_3\, ln\,EI + \beta_4\, ln\,ISU + \beta_5\, ln\,PGDP + \beta_6\, ln\,FDI + \varepsilon$$

$$\ln CI_{it} = \beta_0 + + \beta_1 \ln FD + \beta_2 \ln T + \beta_3 \ln EI + \beta_4 \ln ISU + \beta_5 \ln PGDP + \beta_6 \ln FDI + \rho W \ln CI_{it}$$
$$+ \theta_1 W \ln FD_{it} + \theta_2 W \ln T_{it} + \theta_3 W \ln EI_{it} + \theta_4 W \ln ISU_{it} + \theta_5 W \ln PGDP_{it} + \theta_6 W \ln FDI_{it} + \varepsilon_{it}$$
$$\varepsilon_{it} = \delta W \varepsilon_i + u_{it}, u_{it} \sim i.i.d\left(0, \sigma^2\right) \qquad (8)$$

Where: i —the i-th province, i=1，2，……，30; t — the year; W — the spatial weight matrix; $\beta_0$ — the intercept; $\beta_n$— the coefficient of the n-th explanatory variable, n=1, 2, ……, 6; $\delta$ — the coefficients of the spatial lag terms for the dependent variable; $\theta_m$— the coefficients of the spatial lag terms for explanatory variable, m=1, 2, ……6 ; $\varepsilon_{it}$ — the random variable.

If $\theta = 0$, then the SDM model expressed in equation (7) become a SLM, while if $\theta + \delta\beta = 0$, then equation (7) become a SEM. Otherwise, it is the general SDM.

Though SDM is a general form of both SEM and SLM, Lesage and Pace proved that SDM could not estimate the marginal effects, as accurately as non-spatial models, of the explanatory variables.vii Hence they put forward a partial differential approach to estimate the marginal effects of the variables. Elhorst extended this method into SDM to derive the spatial spillover effects, viii Usually, the effect of an explanatory variable can be divided into the direct and indirect effects.

To derive the direct and indirect effects, we can transform equation (7) into the following expression:

$$D_{it} = (I-\delta W)^{-1}(X_{it}\beta + WX_{it}\theta) + (I-\delta W)^{-1}\nu_i + (I-\delta W)^{-1}\gamma_t + (I-\delta W)^{-1}\varepsilon_{it} \tag{9}$$

Equation (9) could be further transformed into the following matrix by differentiating it with respect to the k-th explanatory variable:

$$\left[\frac{\partial D}{\partial X_{ik}} \times \frac{\partial D}{\partial X_{Nk}}\right] = \begin{bmatrix} \frac{\partial D_1}{\partial X_{ik}} & \bullet & \frac{\partial D_1}{\partial X_{Nk}} \\ \bullet & \bullet & \bullet \\ \frac{\partial D_N}{\partial X_{ik}} & \bullet & \frac{\partial D_N}{\partial X_{Nk}} \end{bmatrix} = (I-\delta W)^{-1} \begin{bmatrix} \beta_k & \omega_{12}\theta_k & \bullet & \omega_{1N}\theta_k \\ \omega_{21}\theta_k & \beta_k & \bullet & \omega_{2N}\theta_k \\ \bullet & \bullet & \bullet & \bullet \\ \omega_{N1}\theta_k & \omega_{N2}\theta_k & \bullet & \beta_k \end{bmatrix} \tag{10}$$

Then, for the k-th explanatory variable in Eq. (10), calculate the mean of the diagonal elements, we can get the direct effect of the k-th explanatory variable. Further, calculate the mean of either the columns or rows, excluding the diagonal, in Eq. (10), we can get the indirect effect of an explanatory variable. It represents the influence of the k-th explanatory variable on the dependent variable of adjacent areas, or the influence of the k-th explanatory variable of adjacent areas on local dependent variable; the total influence of the k-th variable is the sum of the indirect and direct effect.

## RESULTS AND DISCUSSION

### The spatial auto-correlation of Chinese provincial carbon intensity

Calculation results show that Moran's I fluctuate between 0.22 and 0.28 during these 11 years and are all significant at the 1% significance level (Z-score are all greater than 2.58). This illustrates that Chinese provincial carbon intensity is spatially auto-correlated or spatially dependent, instead of randomly distributed. Therefore, spatial effects must be modeled when regressing the impact factors of China's provincial carbon intensity to obtain accurate results in agreement with the practice.

### Results for spatial panel regression

Hausman test was conducted based on the ordinary panel models first. We get a test statistic of 23.17, with a p-value of 0.0016. This illustrates that we should reject the random-effect model, with a 1% significance level. Next, to verify the existence of spatial dependence between variables, we conduct the LM tests. Since the random effect model is rejected, the LM tests should be performed based on the fixed-effect models and mixed-effect model. Thirdly, LM tests were conducted for ordinary panel model with fixed and mixed effects to determine whether the spatial effects should be considered (See Table 2). Table 2 shows that both the mixed effects and individual fixed effects models reject the null hypothesis that there are no spatial lag effects or spatial error effects. This confirms the existence of spatial dependence between the variables in our model. Therefore, spatial econometric models, with maximum likelihood estimation, could be applied to our panel regression since ordinary regression models without considering the spatial interdependence of the variables could give biased or incorrect estimations.

Table 2. LM Test statistics for ordinary panel models when spatial effects are not controlled for.

| Variable | No fixed effects | Space fixed effects | Time fixed effects | Space &time fixed effects |
|---|---|---|---|---|
| R2 | 0.7481 | 0.7445 | 0.6506 | 0.6000 |
| LM-lag | 392.9028*** | 393.5728*** | 121.8332*** | 129.2256*** |
| Robust LM-lag | 822.6972*** | 17．2145*** | 2.5941** | 1.1188* |
| LM-error | 534.1418*** | 531.0611*** | 226.6848*** | 208.1933*** |
| Robust LM-error | 163.9362*** | 154.7028*** | 105.4457*** | 79.0864*** |
| Hausman test=23.6935** | | | | |
| Wald_lag=359.5916*** | | | | |
| Wald_error=12.5817* | | | | |
| LR_lag=214.1663*** | | | | |
| LR_error=11.6696* | | | | |

Note: *, **, *** represent significance at 10%, 5%, and 1% level respectively, for Tables 2-5.

Comparing the test statistics of the four models, it can be deduced that the R2 and Adjusted R2 of the mixed effects model and the individual fixed effects model are the highest, indicating that they give better fits. What's more, the LM-lag, LM-error, Robust LM-lag and Robust LM-error tests for the mixed effects model and the individual fixed effects model are all significant at a significance level of 1% or 5%, while the LM-lag、LM-error test statistics of time fixed effects model and individual-time fixed effects model fail the significance test at 10% significance level. Hence, the mixed effects model and individual fixed effects model are more desirable. However, some research suggest fixed effects models are more appropriate and robust in economic regressions most of the time. Therefore, individual fixed effect model is selected as our panel regression model.

The LM test statistics in Table 2 support the use of spatial econometric models in our investigating the effect of financial development on carbon intensity. Hence, SDM is applied to studying their relationship, controlling other variables. Table 2 illustrates both the estimation results and related tests statistics. We see that the R2 is 0.86 originally for ordinary fixed effects model (See Table 2) when spatial effects were not taken into account in the regression; however, it improved to be 0.9094 (in Table 4) when spatial effects were taken into account, with obviously superior fitness. Meanwhile, we undertook Wald-lag, LR_lag,Wald_error, and LR_error tests to see if the spatial Durbin model could be reduced to either SLM or SEM, and the test statistics, all significant at 1% level, prove that SDM can be reduced to neither. Hence, spatial Durbin model should be used as the regression model.

**Results of spatial Durbin estimation**

The spatial Durbin model regression results are shown in Table 3. The test statistics of SDM are shown in Table 4.

Table 3. Estimation and test results: impact of FI on CO2.

| Variable | Coefficient | T-statistics | Z-probability |
|---|---|---|---|
| lnFI | 0.1321** | 2.5427 | 0.0110 |
| LnPGDP | -0.0496 | -0.4582 | 0.6468 |
| lnIS | -0.3657*** | -5.9797 | 0.0000 |
| lnUL | 0.8705*** | 4.5600 | 0.0000 |
| lnP | -0.1252*** | -3.2754 | 0.0011 |
| lnEC | 1.1331*** | 14.3523 | 0.0000 |
| W*lnFI | -0.1635** | -2.2817 | 0.0225 |
| W*lnPGDP | 0.1646 | 1.0777 | 0.2812 |
| W*lnIS | 0.4455*** | 5.1754 | 0.0000 |
| W*lnUL | -0.8261*** | -3.4461 | 0.0006 |
| W*lnP | 0.1791*** | 3.9761 | 0.0001 |
| W*lnEC | -0.9339*** | -9.9639 | 0.0000 |
| W*dep.var. | 0.9100*** | 61.8241 | 0.0000 |
| R2=0.9467 | | | |
| Log-likelihood=136.4405 | | | |

Table 4. Estimation results: the moderating role of industrial structure

| Variable | Coefficient (Model 11) | Coefficient (Model 12) |
|---|---|---|
| lnFI | 0.1321** | 0.1825*** |
| LnPGDP | -0.0496 | 0.0718 |
| lnIS | -0.3657*** | -0.1191* |
| lnUL | 0.8705*** | 0.5057** |
| lnP | -0.1252*** | -0.1525*** |
| lnEC | 1.1331*** | 1.0842*** |
| lnFI*lnIS | | -0.1479*** |
| R2 | 0.9467 | 0.9490 |

Table 3 illustrates that the local province's carbon intensity increases with local financial development, FDI, and energy intensity from 2007 to 2017, while decreases with local technology. However, local affluence and economic structure do not affect local carbon intensity significantly. Further, adjacent areas' financial development, FDI, and industrial structure upgrading significantly curbs local carbon emissions while adjacent areas' affluence and technology significantly increase local emissions. Lastly, adjacent areas' energy intensity has no spatial spillover effects.

Table 4 shows that the R2 of SDM regression results improved to 0.9094, better than the results when no spatial effects are considered. Further, the Log-L of the SDM improved from the original 15.63 to 79.6376, apparently improved. The four tests: Wald_lag, Wald_error, LR_lag, LR_error, all rejected the hypothesis that spatial Durbin model could be reduced to SLM or SEM. Therefore, the appropriateness of spatial Durbin model is proved. The spatial Durbin model should be used in the regression.

However, as mentioned above, the coefficients derived according to our spatial Durbin model in Table 2, could not show the marginal influence of the explanatory variables on the dependent variable. Hence, we apply equation (10) and calculate the mean of the diagonal elements to get the direct effect of the k-th explanatory variable. Further, calculate the mean of either the columns or rows, excluding the diagonal, in Eq. (10), to get the indirect effect of an explanatory variable. Finally, we sum up the indirect and direct effect to get the total influence of the k-th variable. The direct, indirect, and total effects of the variables are shown in Table 5.

Table 5. Estimation results: mediation effect of urbanization

| Variable | Model （16） PCO2 | Model （17） UL | Model （18） PCO2 |
|---|---|---|---|
| lnFI | 0.2066($\tau_1$)*** | 0.0954($\psi_1$)*** | 0.1321($\zeta_1$)** |
| LnPGDP | 0.2280** | 0.3064*** | -0.0496 |
| lnIS | -0.4188*** | -0.0591*** | -0.3657*** |
| lnUL | | | 0.8705($\zeta_2$)*** |
| lnP | -0.1249*** | 0.0008 | -0.1252*** |
| lnEC | 1.2270*** | 0.1063*** | 1.1331*** |
| R2 | 0.9459 | 0.9724 | 0.9467 |

**The effect of financial development on carbon intensity**

China is rigorously promoting its urbanization and its transportation. As a result, the Chinese society is beginning to become one with rather mobile population, which further resulted in fast and frequent movement of production factors. The moving of production factors and resources, in turn, can impact the economic structure, economic growth, and carbon emissions significantly in China. As a production factor, financial resource is still not abundant enough in China. Further, financial resources play crucial allocation roles in distributing resources to where they flow into: all the other production factors, such as labor, will follow where financial resources flow into. Therefore, where the financial resources is directed into is of vitally importance in the upgrading of economic structure and carbon emissions, and in the realization of a “both good and fast growth”.

Table 5 illustrates that since 2007, local provinces’ financial development is significantly (one percent significance level) positively related to local carbon emissions and at the same time significantly negatively related to (one percent significance level) adjacent areas’ emissions. The local province will suffer an increase by 0.1918% in local carbon intensity while the adjacent areas will enjoy a decrease by 0.7264% in their carbon intensity, for every one percent increase in local financial development. The total effect is -0.5346, significant at one percent significance level. This reveals that a net decrease by 0.5346% in the carbon intensity of the country as a whole will be resulted when there is one percent increase in a local province’s financial development. According to the three mechanisms through which financial development can affect carbon emissions introduced in the introduction section, the result that local financial development contributes to improve local emissions should be caused by the consumption effect and production expansion effect. This means that local finance resources were not channeled to technological innovation projects as they should, but were channeled into consumption and firms production, so that local citizens had more funds to purchase more energy-consuming goods such as cars, air conditioners, and so that local enterprises gained sufficient financial resources to produce more. The increase in local production and consumption resulted in more energy consumed and more carbons emitted locally. On the other hand, as local economic activity expanded and local living standards improved, adjacent working age people move to local enterprises for better jobs, more income and better living conditions. As a result of people flowing out of neighboring areas’ and into local areas, two effects were resulted. First, more carbon is emitted in the local area because of expanded production and a larger population. Second, neighboring areas enjoyed less carbon emissions because of a decreased population. As a result of more reductions in carbon emissions experienced by neighboring areas than the increase in emission in the local area, which might be caused by economies of scale: much more resources will be consumed when people are scattered than clustered, the nation will enjoy a decrease in its emissions as a whole for an improved financial development in one local province.

Table 5 shows that from 2007 to 2017, both the direct effect and total effect of industrial upgrading are insignificant. Though there is only a weak curbing indirect effect, we do not interpret a 10% significance level as significant, considering the insignificant direct and total effects. As mentioned before, China has officially and intentionally strived to upgrade its industrial structure to protect the environment and to achieve a “both good and fast” economic growth. However, our model does not reveal a significant relationship as expected. If the related policies have taken effects, there should be a significant relationship between its industrial structure upgrading and emissions. Therefore, considering China’s endeavors of upgrading its industrial structure, we think there is no effect of this measure in reducing emissions, neither in reducing local emissions nor in reducing emissions in the country as a whole. According to the channels that industrial structure upgrading may affect carbon emissions mentioned in section one, we think the insignificant effect of industrial structure upgrading on carbon emissions might be a result of two causes. First, it may be that the industrial structure upgrading had not played any significant role in reducing emissions, in saving energies, or in upgrading firms from energy-intensive to capital-intensive or knowledge-intensive ones at all. Taking into consideration of the role that financial resources could place in industrial structure upgrading, we might infer that financial resources were not channeled into technological innovations and upgrading of industrial structures. This may be witnessed as a failure of government policy in achieving a “both good and fast” economic growth through industrial structure upgrading. Second, this may suggest that there have been not sufficient less-energy consuming firms replacing energy-intensive firms to reduce emissions as China wished. In other words, there were some firms transforming from energy-intensive to capital-intensive and knowledge-intensive firms, which contributed to a reduction in emissions. However, as there were simultaneously some farmers transforming into factory workers who worked in labor-intensive or energy-intensive firms, more carbon was emitted as the primary production were replaced by industrial production. As the two effects offset, we did not evidence any significant relationship between the two variables. This shows that its industrial structure upgrading policy has begun to achieve some effect in realizing a “both good and fast” growth, but its effect were not sufficient, either as a result of the short time period studied or as a result of no in-depth policy measures taken. This means China should carry on with or deepen its current industrial structure upgrading policy to reap its benefits in the future. Anyway, China should direct its financial resources into capital-intensive and knowledge-intensive firms to upgrade its industrial structure to realize a “both good and fast” growth.

## CONCLUSIONS

Using China’s provincial data from 2007 to 2017, the paper investigates the effect of financial development and industrial upgrading on carbon intensity. Firstly, China’s provincial carbon emissions are calculated. Then, the effect of financial development and industrial structure upgrading on China’s carbon intensity is investigated by using the Spatial Durbin Model. The following conclusions are derived. Firstly, viewed from the perspective of the local provincial, financial development, energy intensity and FDI are significantly positively related to local carbon emissions, while technology is significantly negatively related to the local province’s emissions. However, viewed from the national economy as a whole, financial development obvious curbs CO2 emissions. Meanwhile, energy intensity and economic development significantly contribute to CO2 emissions. Secondly, although financial development curbs carbon emissions in China since the recent financial crisis. Overall speaking, this curbing effect is not realized through the direct effect, which is positive and shows financial development increases local carbon emissions. This illustrates that the financial development affects emissions essentially through the consumption and production effect instead of the technology innovation effect. Hence, financial resources were essentially not allocated to technological innovations and R&D of enterprises to promote the new technologies to save non-recycling resources and reduce emissions. Thirdly, industrial structure upgrading since 2007, especially the replacing of energy-intensive firms by less energy-consuming or hi-tech firms, was not placing its role fully in achieving a low-carbon economy as wished. Taking into consideration of the role that financial resources could place in industrial structure upgrading, we might infer that financial resources were not sufficiently channeled into technological innovations or capital-intensive or knowledge-intensive to achieve upgrading of its industrial structures.

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