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RESEARCH ARTICLE

# How does industrial structure transformation affect carbon emissions in China: the moderating effect of financial development

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## Abstract

Given China's rapid industrial upgrade and economic development process, this study tries to explore the effect of industrial structure transformation on carbon emissions in China and the moderating effect of financial development by employing the traditional OLS model, the dynamic SYS-GMM model, and the dynamic spatial lag model comprehensively. In particular, industrial structure transformation has been divided into two indicators including industrial structure rationalization and industrial structure optimization; carbon emissions are evaluated from the dual perspective of scale and average. The empirical results indicate that only industrial structure optimization has a negative impact on carbon emissions scale in China at the national level. In addition, financial development has merely and positively moderated the nexus between industrial structure rationalization and carbon emissions scale and per capital carbon emission in the southern regions of China, which highlights the establishment of regional heterogeneity and the necessity of formulating policy in line with local conditions. Both theoretical and practical significance have drawn from this study, for the emerging economics and in particular for China, to reduce carbon emissions through industrial structure transformation and financial development and promote high-quality development in the new era.

**Keywords** Industrial structure transformation · Carbon emissions · Moderating effect · Financial development · Spatial spillover effect

## Introduction

Along with the increase of global environmental issues, especially global warming, policymakers worldwide prioritize greenhouse gas emissions reduction to adjust climate change, especially highlighting carbon emissions (Cuesta et al. 2021). In order to control greenhouse gas emissions and combat against global climate change, past research has provided rich descriptions of the complex relationship between carbon emissions and industrial structure (Mi et al. 2015; Zhang et al. 2019), trying to find how to reduce the carbon emissions through industrial structure transformation. However, due to the coexistence of the emission reduction effect and the energy rebound effect, it is difficult to prejudge the complex relationship between industrial structure transformation and carbon emissions (Li and Solaymani 2021). Faced with the dilemma of achieving industrial structure transformation and mitigating carbon emissions in developing countries, it is of important theoretical and practical significance to reveal the influencing mechanism between industrial structure transformation and carbon emissions. That may benefit for helping policymakers to coordinate the sustainable development between industrial structure transformation and carbon emissions.

In addition, financial development can spur economic growth by lowering financial cost, boosting investment scale, stimulating technology/knowledge spillover, as well as promoting total factor productivity, which has not only caught a profound impact on people's living standards, but also caught widespread attention from academics around the world (Alam and Paramati 2015). Due to the comprehensive impact of financial development on the economic system, the differentiation of its emphasis field will have a differentiated impact on

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carbon emissions (Li et al. 2019). However, the moderating effect of financial development has been ignored, which creates further research to explore its moderating effect on reducing the carbon emissions and provides a new insight for this study.

Responding to these research gaps, we focus our research on (1) how the carbon emissions can mitigate through adjusting industrial structure transformation?, (2) does financial development has an effect on the complex relationship between industrial structure transformation and carbon emissions?, and (3) and how financial development affect this complex relationship?

As for the research method, the existing papers mainly conducted regressions by using traditional ordinary least squares (OLS) method, ignoring the dynamic effect and the spatial spillover effect of carbon emissions (Liu and Zhang 2021). Due to the potential endogeneity problems in the estimation process, it is important and necessary to select appropriate econometric approaches. The conventional approach to deal with the endogeneity problem is the instrumental variable (IV) method, while the two requirements of exogenesis and correlation are often contradictory, which forms the obstacle of selecting an ideal IV (Perutka 2008). Thus, the lag terms of independent variables are often used as the instrumental variable (IV) in practice (Qu et al. 2020). Hence, this study attempts to employ the system-generalized method of moments (SYS-GMM) as the estimation method for the dynamic regression model, which has the advantage in addressing potential endogeneity and weak instrumental problems compared with the difference-generalized method of moments (DIF-GMM) method (Qu et al. 2020). Furthermore, this study will also employ the dynamic spatial lag model as an in-depth research to investigate the coexistence of the dynamic effect and the spatial spillover effect of carbon emissions simultaneously (Li and Li 2021).

China is a vast country with rapid economic development, industrial structure, and resource endowment varying dramatically across regions, to address the estimations based on the whole sample subject to regional disparity biases and improve the level of local carbon reduction policies; this study will divide the entire sample by region and examines the estimation in different regions respectively and propose relative policy recommendations accordingly (Zhang and Guo 2016). Based on the traditional OLS method, the dynamic regression method, and the dynamic spatial lag method, this study comprehensively investigates the effect of industrial structure transformation on carbon emissions scale and per capita carbon emission in China at national and regional levels, considering the moderating effect of financial development. This study provides an explanation on the complex relationship among industrial structure transformation, carbon emissions, and financial development, which aims to extend the research of sustainable development.

The remaining structure of this study proceeds as follows. “Literature review and comments” section gives the literature review of this study. “Methodology” section presents the methodology of this study, including variables selection, data source, and model specification. “Empirical results and analysis”section interprets our empirical results and analysis. Finally, we draw the conclusions of this study and provide policy recommendations in “Conclusions and policy recommendations” section.

## Literature review and comments

### Carbon emissions

Extant literature pertaining to carbon emissions at industrial and regional levels has recognized that the combustion of fossil fuels and the industrial production predominantly cause the increase of it (Friedl and Getzner 2003; Hou et al. 2018; Sueyoshi and Goto 2014; Zhang and Gao 2016). These studies have examined the impact of the combustion of fossil fuels and the industrial structure by using case study (Mi et al. 2015), regression analysis (Shao et al. 2019; Su and An 2018), and theoretical modeling (Barbulescu 2017; Yu and Zhang 2021), respectively. For instance, Sueyoshi and Goto (2014) studied the relationship between the combustion of fossil fuels and carbon emissions by using the DEA model; the results showed that improving energy utility does have a significant effect on decreasing carbon emissions; Shan et al. (2016) employed apparent energy consumption approach for testing emissions factors during 2000–2012 in China and reduced the uncertainty on Chinese carbon emissions estimate; Yu and Zhang (2021) proposed that the main empirical strategy for estimating the carbon emissions efficiency are difference-in-differences (DID) and spatial difference-in-differences (SDID) estimators.

However, how to decrease the amount of carbon emissions through adjusting industrial structure remains as a black box (Hou et al. 2018; Mi et al. 2015; Wang 2012). On the one hand, a stream of literature claims that the relationship between industrial structure and carbon emissions affects by technological progress, environmental regulation, and economic development. For example, Mi et al. (2015) found that industrial structure adjustment can save energy and reduce carbon emissions, and this positive effect will change because of the annual growth rate of GDP and finance; While Hou et al. (2018) found that the industrial green transformation on decreasing carbon emissions is limited by the “critical mass” of environmental regulations. On the other hand, some scholars have attempted to verify and upgrade existing research by exploring the essential role of spatial spillover effects. For instance, Wang et al. (2020) studied the spatial spillover effects of fiscal decentralization, industrial structure on energy efficiency by using the spatial Durbin model, and found that fiscal decentralization has a positive effect on the energy efficiency of the eastern and central regions by upgrading the industrial structure; Wang et al. (2019) examined the positive impact of the industrial structure on carbon emissions, and revealed how this positive impact changes because of the spatial spillover effects.

## Industrial structure transformation

Industrial structure transformation is an essential outcome along with the advancement of industrialization processes, showing an overall trend that the secondary sector develops slowly while the tertiary sector develops quickly (Tian et al. 2014). Industrial structure transformation is critical for developing sustainable ability and decreasing carbon emissions since the traditional industrial structure is no longer suitable for environmental-friendly demands (Zhang et al. 2019). Increasing researchers pay more attention to the relationship between industrial structure transformation and carbon emissions (Han et al., 2016; Mi et al. 2015; Zhang et al. 2019). In particular, Hou et al. (2018) found industrial green transformation had a threshold effect on decreasing carbon intensity and moderated by the environmental regulations; Tian et al. (2019) applied a framework to explore the impact of industrial structure change on carbon emissions in the Chinese southwest economic zone, and found that the diversification in development and competitive industries had different impacts on carbon emissions; Guo et al. (2021) claimed that the upgrading and optimization of industrial structure is an effective approach to decrease carbon emissions.

Previous research has tested the impact of industrial structure transformation on carbon emissions through highlighting the sectorial proportion change at the national and regional levels (Zhang et al. 2019). In addition, some research has tested and enriched existing empirical results by redefining and accurately describing the meaning of industrial structure transformation from sectoral perspectives (Guo et al. 2021). For example, industrial structure rationalization and industrial structure optimization are often used to estimate the level of industrial structure transformation, and which are conducive for promoting green productivity (Lu et al. 2020; Guo et al. 2021; Li et al. 2019). Thus, the industrial structure transformation in this study has been divided into two sections, such as industrial structure optimization and industrial structure rationalization, respectively. Specifically, industrial structure optimization is defined as the allocation and the flow of resources which benefit for achieving the goal of coordinated development (Javadi et al. 2016), while industrial structure rationalization refers to the reallocation of production resources to the upper industry and the upgrading of economic leading industries (Lu et al. 2020).

## Financial development

Financial development is an effective indication of the financial intermediation; it provides a platform for listed companies to reduce the cost of capital by increasing financial channels and optimizing liability structure (Alam and Paramati 2015). Until now, financial development has been applied as an indicator to describe the causal relationship between economic investment and energy efficiency (Al-mulali and Sab 2018). Previous researchers show that financial development has a considerable impact on energy consumption and carbon emissions as it encourages more manufacturing production activities leading to more carbon emissions (Sadorsky 2010; Zhang 2011). Along with the discussion about the impact of financial development on carbon emissions, researchers gradually find its negative effect by using the generalized multivariate model, the bivariate model, and the error correction model (Jalil and Feridun 2011; Kumbaroglu et al. 2008; Tamazian et al. 2009).

Nowadays, several interesting insights about financial development emerge in the process of researching the effects of industrial structure transformation on carbon emissions (Li et al. 2019). For instance, high level of financial development has brought increasing investment into industrial transformation, achieving the optimal allocation of production factors within and across the organization, and then increase the positive effect of industrial structure transformation on green development (Koch 2014). In addition, financial development not only benefits for accelerating industrial structure transformation by regulating resource allocation, indirectly affecting the carbon emissions falling process, but also for providing more capital to environmental governance that directly decrease carbon emissions (Hou et al. 2018).

### Literature comments

Although a wide range of literature has discussed the relationship among industrial structure transformation, financial development, and carbon emissions, there still exists uncertainty and should be further explored. On the one hand, in order to synthetically investigate the effects of industrial structure transformation on carbon emissions, the industrial structure transformation in this study had been divided into two indicators including industrial structure rationalization and industrial structure optimization, and the carbon emissions in this study had also been divided into two indicators including carbon emissions scale and per capita carbon emission. On the other hand, few studies examine the moderating effect of financial development on the relationship between industrial structure transformation and carbon emissions. In addition, the dynamic and spatial spillover effects should also be considered in empirical analysis. Furthermore, the regional heterogeneity should not be ignored to gain precise policy implications. Therefore, in order to fill these gaps, this study attempts to investigate the effects of industrial structure transformation on carbon emissions in China and the moderating effect of financial development at national and regional levels from dual perspectives of space and time.

## Methodology

### Variables selection

(1) Dependent variables

In this study, the dependent variables can be divided into two indicators that are measured by carbon emissions scale (*CS*) and per capita carbon emission (*PC*), respectively. To measure the amount of carbon emissions scale (*CS*) in each province, this study has adopted the standard proposed by the Intergovernmental Panel on Climate Change (IPCC) in 2006. In particular, the annual consumption amount of coal, diesel, natural gas, kerosene, fuel oil, crude oil, and coke in each region is employed to calculate the amount of carbon emissions scale (*CS*). In addition, the ratio of the amount of carbon emissions scale (*CS*) to the total number of people is employed to act as the proxy indicator of per capita carbon emission (*PC*).

(2) Key explanatory variable

Referring to the research of Li et al. (2019), this study measured industrial structure rationalization (*ISR*) by adopting the reciprocal of the Theil index.

$$ISR = 1/\sum_{i=1}^{n}\left(\frac{O_i}{O}\right)\ln\left(\frac{O_i}{L_i}/\frac{O}{L}\right) = 1/\sum_{i=1}^{n}\left(\frac{O_i}{O}\right)\ln\left(\frac{O_i}{O}/\frac{L_i}{L}\right) \quad (1)$$

where $O$ and $L$ denote the total output and employment of the three industries respectively, $O_i$ and $L_i$ are the output and employment respectively of the industry $i$. If the value of $O_i/L_i$ equals to that of $O/L$, the logarithmic value of it is 0, that is, the industrial structure is reasonable and in a balanced state, which means that resources are optimally allocated among the three industries. However, due to the limitation of resources specificity, labor productivity cannot be the same across the three industries, that is, the deviation from equilibrium is normal for the economy, especially in developing countries. In particular, the greater value of *ISR*, the more rational of the industry structure.

In the process of industrial structure optimization (*ISO*), the secondary category gradually transfers to the third/service category. Hence, this study uses the ratio of employment in the tertiary industry to the secondary industry to represent industrial structure optimization. In particular, the greater value of *ISU*, the more advanced of the industry structure.

(3) Moderating variable

To reveal the moderating effect of financial development (*FD*) in the process of industrial structure transformation (i.e., *ISR* and *ISO*, respectively) affecting carbon emissions (i.e., *CS* and *PC*, respectively), the ratio of the annual added value in the finance industry to GDP is applied to represent financial development.

(4) Control variables

In this study, six control variables are employed to capture the characteristic of each province by referring to the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model, which is widely used in the field of carbon emissions issues. For instance, economic development (*ED*) is measured by GDP per capita; human capital (*HC*) is measured by the average educated year of employed persons; urbanization level (*UL*) is measured by the ratio of urban population to total population; technical innovation (*TI*) is measured by the patent counts; energy consumption structure (*ECS*) is measured by the share of fossil fuel consumption in the total energy consumption; degree of opening up (*FDI*) is measured by the ratio of foreign direct investment to GDP in each province.

### Data source

This study investigates the effects of industrial structure transformation on carbon emissions and the moderating effect of financial development by employing the annual data of 30 provincial areas (i.e., provinces, autonomous regions, and municipalities directly under the central government) scanning from 2000 to 2018. Due to the lack of corresponding data, Tibet, Macao, Hong Kong, and Taiwan are excluded from the research sample. The data are collected from several sources, including *China Statistical Yearbook*, *China Energy Statistical Yearbook*, and the *Statistical Yearbooks* of each province. By setting industrial structure transformation as the transition variable, this study investigates the impact of industrial structure transformation on carbon emissions in China and the moderating effect of financial development, as well as that of its two regions: the northern region (Heilongjiang, Jilin, Liaoning, Inner Mongolia, Xinjiang, Gansu, Qinghai, Ningxia, Shanxi, Shannxi, Hebei, Tianjin, Beijing, Shandong, Henan) and the southern region (Jiangsu, Chongqing, Sichuan, Hubei, Shanghai, Anhui, Zhejiang, Jiangxi, Hunan, Guizhou, Yunnan, Fujian, Guangdong, Guangxi, Hainan). Sample statistics are described in Table 1.

### Model specification

The relationship between industrial structure transformation and carbon emissions is at first analyzed using the

**Table 1** Statistical description of variables

| Variables | Units | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|---|
| *CS* | $10^4$ ton | 9.678 | 0.770 | 6.658 | 11.191 | 9.678 |
| *PC* | Ton per capita | 1.519 | 0.561 | −0.061 | 2.859 | 1.519 |
| *ISR* | - | −3.152 | 43.391 | −937.044 | 96.486 | −3.152 |
| *ISO* | - | 4.664 | 0.375 | 3.948 | 6.219 | 4.664 |
| *FD* | % | 1.512 | 0.503 | 0.028 | 2.889 | 1.512 |
| *ED* | CNS | 10.054 | 0.835 | 7.923 | 11.939 | 10.054 |
| *HC* | Year | 2.132 | 0.126 | 1.693 | 2.540 | 2.132 |
| *UL* | % | 3.868 | 0.300 | 3.144 | 4.495 | 3.868 |
| *TI* | Piece | 8.827 | 1.707 | 4.248 | 13.078 | 8.827 |
| *ECS* | % | 3.755 | 0.467 | 0.490 | 4.416 | 3.755 |
| *FDI* | % | 0.454 | 1.053 | −3.217 | 2.684 | 0.454 |

conventional OLS method with dual fixed effects of time and individual.

$$Y_{it} = \alpha_0 + \beta_1 X_{it} + \gamma C_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{2}$$

where $Y_{it}$ denotes the dependent variable, $\alpha_0$ denotes the constant term, $X_{it}$ denotes the key explanatory variable, and $\beta_1$ denotes the coefficient of it. $C_{it}$ denotes a vector of control variables and denotes the coefficients of them. $\lambda_i$ and $\mu_t$ denote the individual fixed effect and the time fixed effect, respectively. $\varepsilon_{it}$ denotes the disturbance term.

In addition, to gain deeper insight into the moderating effect of financial development (*FD*) between the nexus of industrial structure transformation (i.e., *ISR* and *ISO*, respectively) and carbon emissions (i.e., *CS* and *PC*, respectively), the interactive term of financial development (*FD*) and industrial structure transformation (i.e., *ISR* and *ISO*, respectively) is included in Eq.(2).

$$Y_{it} = \alpha_0 + \beta_1 X_{it} + \beta_2 M_{it} + \beta_3 X_{it} {*} M_{it} + \gamma C_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{3}$$

where $M_{it}$ denotes the moderating variable, $\beta_2$ denotes the coefficient of it, and the other parameters are consistent with Eq.(2).

$$Y_{it} = \alpha_0 + \tau Y_{i,t-1} + \beta_1 X_{it} + \gamma C_{it} + \varepsilon_{it} \tag{4}$$

Furthermore, to further investigate the dynamic effect of the dependent variable, we include the temporal lag term of it in Eq.(2) and Eq.(3), respectively.

$$Y_{it} = \alpha_0 + \tau Y_{i,t-1} + \beta_1 X_{it} + \beta_2 M_{it} + \beta_3 X_{it} {*} M_{it} + \gamma C_{it} + \varepsilon_{it} \tag{5}$$

where $Y_{i,t-1}$ denotes one phrase lag of the dependent variable, $\tau$ denotes the coefficient of it, and the other parameters are consistent with Eq.(3). Additionally, to solve the errors caused by the endogenous problem, the SYS-GMM method is employed in the estimation.

Last but not least, to further explore the spatial effect of the dependent variable, we also include the spatial lag term of it in Eq.(4) and (5), respectively. In particular, the dynamic spatial lag model with dual fixed effects of time and individual is utilized here after the LR joint significance tests with time and space, respectively.

$$Y_{it} = \rho W Y_{it} + \tau Y_{i,t-1} + \beta_1 X_{it} + \gamma C_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{6}$$

$$Y_{it} = \rho W Y_{it} + \tau Y_{i,t-1} + \beta_1 X_{it} + \beta_2 M_{it} + \beta_3 X_{it} {*} M_{it} + \gamma C_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{7}$$

where $W$ denotes the first-order adjacency weight matrix, $\rho$ denotes the spatial autoregressive coefficient of the dependent variable, and the other parameters are consistent with the former equations. To eliminate the potential problem of collinearity, all the interactive items in this study are centralized.

## Empirical results and analysis

### Benchmark regression results analysis

The estimated results of the benchmark OLS model with individual and time fixed effects are showed in Table 2. As shown in Table 2, all the coefficients of industrial structure rationalization are significantly positive in columns (1), (5), and (6), positive but insignificant in column (2), while all the four absolute values of them nearly equal to zero; in other words, industrial structure rationalization has a relatively positive but weak impact on carbon emissions (i.e., carbon emissions scale and per capita carbon emission) in China. In addition, all the coefficients of industrial structure optimization in columns (3), (4), (7), and (8) are significantly negative; in other words, industrial structure optimization has a negative impact on carbon emissions (i.e., carbon emissions scale and per capita carbon emission) in China. All the coefficients of the interactive terms of the key independent variables and the moderating variable (i.e., *ISR*FD* and *ISO*FD*) are insignificant in columns (5)–(8); in other words, the moderating effect of financial development in the process of industrial structure transformation (i.e., industrial structure rationalization and industrial structure rationalization) affecting carbon emissions (i.e., carbon emissions scale and per capita carbon emission) is not supported under the static scenarios.

### Dynamic regression results analysis

The estimated results of the dynamic SYS-GMM model are showed in Table 3. In particular, to test the validity of instrumental variables, this study has employed the Arellano-Bond

**Table 2** Benchmark regressive results of the whole sample

| Variables | *CS* (1) | *PC* (2) | *CS* (3) | *PC* (4) | *CS* (5) | *PC* (6) | *CS* (7) | *PC* (8) |
|---|---|---|---|---|---|---|---|---|
| *ISR* | 0.000* | 0.000 | | | 0.000* | 0.000* | | |
| | (1.729) | (1.555) | | | (1.900) | (1.738) | | |
| *ISO* | | | −0.120*** | −0.175*** | | | −0.161*** | −0.227*** |
| | | | (−2.676) | (−3.962) | | | (−3.246) | (−4.634) |
| *FD* | | | | | 0.016 | 0.016 | 0.069* | 0.091** |
| | | | | | (0.458) | (0.472) | (1.814) | (2.447) |
| *ISR*FD* | | | | | 0.001 | 0.001 | | |
| | | | | | (0.801) | (0.781) | | |
| *ISO*FD* | | | | | | | 0.084 | −0.020 |
| | | | | | | | (1.628) | (−0.399) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 570 | 570 | 570 | 570 | 570 | 570 | 570 | 570 |
| $R$-squared | 0.844 | 0.820 | 0.845 | 0.824 | 0.845 | 0.820 | 0.847 | 0.826 |

*t*-statistics in parentheses; ***$p$<0.01, **$p$<0.05, *$p$<0.1

and Sargan tests in dynamic panel data analysis. As shown in Table 3, all the $p$ values of the first-order and second-order differences are lower and higher than 0.1, respectively, implying that there is no serial correlation problem in this study. In addition, the $p$ values of the Sargan test are higher than 0.1, indicating that there is no over-identification

**Table 3** Dynamic regressive results of the whole sample

| Variables | *CS* (1) | *PC* (2) | *CS* (3) | *PC* (4) | *CS* (5) | *PC* (6) | *CS* (7) | *PC* (8) |
|---|---|---|---|---|---|---|---|---|
| *L.CS* | 0.695*** | | 0.640*** | | 0.605*** | | 0.559*** | |
| | (21.228) | | (9.923) | | (12.504) | | (9.272) | |
| *L.PC* | | 0.390*** | | 0.336*** | | 0.407*** | | 0.293*** |
| | | (10.773) | | (8.397) | | (8.740) | | (5.478) |
| *ISR* | −0.000*** | −0.000*** | | | −0.001* | −0.000** | | |
| | (−3.521) | (−3.762) | | | (−1.923) | (−2.534) | | |
| *ISO* | | | −0.337*** | −0.209*** | | | −0.202*** | −0.304*** |
| | | | (−7.759) | (−5.221) | | | (−3.558) | (−5.204) |
| *FD* | | | | | −0.243*** | 0.018 | −0.152*** | 0.111*** |
| | | | | | (−8.031) | (0.527) | (−3.514) | (6.693) |
| *ISR*FD* | | | | | 0.002* | −0.000** | | |
| | | | | | (1.783) | (−2.493) | | |
| *ISO*FD* | | | | | | | 0.163*** | 0.071 |
| | | | | | | | (3.338) | (1.400) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| AR(1) | [0.096] | [0.088] | [0.090] | [0.075] | [0.074] | [0.087] | [0.087 | [0.089] |
| AR(2) | [0.232] | [0.216] | [0.239] | [0.197] | [0.239] | [0.215] | [0.228] | [0.200] |
| Sargan | [1.000] | [1.000] | [1.000] | [1.000] | [1.000] | [1.000] | [1.000] | [1.000] |
| Observations | 540 | 540 | 540 | 540 | 540 | 540 | 540 | 540 |

*z*-statistics in parentheses; $p$ values in square brackets; ***$p$<0.01, **$p$<0.05, *$p$<0.1

**Table 4** Dynamic spatial regressive results of the whole sample

| Variables | *CS* (1) | *PC* (2) | *CS* (3) | *PC* (4) | *CS* (5) | *PC* (6) | *CS* (7) | *PC* (8) |
|---|---|---|---|---|---|---|---|---|
| *L.CS* | 0.453*** | | 0.480*** | | 0.442*** | | 0.468*** | |
| | (14.569) | | (16.199) | | (13.988) | | (15.252) | |
| *L.PC* | | 0.473*** | | 0.471*** | | 0.459*** | | 0.454*** |
| | | (15.134) | | (15.138) | | (14.375) | | (14.238) |
| *ISR* | −0.000 | −0.000 | | | −0.000 | −0.000 | | |
| | (−1.340) | (−1.480) | | | (−1.254) | (−1.392) | | |
| *ISO* | | | −0.160*** | −0.004 | | | −0.160*** | −0.009 |
| | | | (−3.106) | (−0.073) | | | (−2.927) | (−0.182) |
| *FD* | | | | | 0.053* | 0.063** | 0.054* | 0.066** |
| | | | | | (1.724) | (1.994) | (1.770) | (2.062) |
| *ISR*FD* | | | | | −0.000 | −0.000 | | |
| | | | | | (−0.250) | (−0.269) | | |
| *ISO*FD* | | | | | | | 0.005 | 0.038 |
| | | | | | | | (0.140) | (1.012) |
| $\rho$ | −0.042** | −0.017 | −0.054** | −0.023 | −0.045*** | −0.023 | −0.044* | −0.015 |
| | (−2.402) | (−1.192) | (−2.481) | (−1.366) | (−2.596) | (−1.587) | (−1.926) | (−0.862) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 540 | 540 | 540 | 540 | 540 | 540 | 540 | 540 |
| *R*-squared | 0.273 | 0.854 | 0.268 | 0.825 | 0.208 | 0.796 | 0.340 | 0.841 |

*z*-statistics in parentheses; ***$p$<0.01, **$p$<0.05, *$p$<0.1

problem in this study. For the lag term of the dependent variables, all the coefficients of them are significantly positive; in other words, the temporal inertia of carbon emissions (i.e., carbon emissions scale and per capita carbon emission) has a positive impact on the current period of it. For the key independent variables (i.e., *ISR* and *ISO*), all the coefficients of them are significantly negative; in other words, with the consideration of dynamic effect, industrial structure transformation has a negative impact on carbon emissions (i.e., carbon emissions scale and per capita carbon emission). For the interactive terms of the key independent variables and the moderating variable (i.e., *ISR*FD* and *ISO*FD*), the coefficients of *ISR*FD* in column (5) and *ISO*FD* in column (7) are significantly positive; the coefficient of *ISR*FD* in column (6) is significantly negative, while the coefficients of *ISO*FD* in column (7) are positive but insignificant; in other words, financial development has a negative moderating impact on the process of industrial structure transformation affecting carbon emissions scale, and a positive moderating impact on the process of industrial structure rationalization affecting per capita carbon emission, while the moderating effect of it on the process of industrial structure optimization affecting per capita carbon emission is relative weak.

## Dynamic spatial regression results analysis

The estimated results of the dynamic spatial lag model are showed in Table 4. As shown in Table 4, all the dynamic lag coefficients of the dependent variables in columns (1)–(8) are significantly positive; in other words, the temporal inertia of carbon emissions (i.e., carbon emissions scale and per capita carbon emission) has a positive impact on the current period, no matter with or without the consideration of the spatial spillover effect. In addition, all the spatial autoregressive coefficients of the dependent variables are significantly negative in columns (1), (3), (5), and (7), negative but insignificant in columns (2), (4), (6), and (8); in other words, the spatial spillover effect has to some extent reduced carbon emissions in China, while this reduction effect on carbon emissions scale is obviously stronger than that on per capita carbon emission. For the key independent variables (i.e., *ISR* and *ISO*), all the coefficients of *ISR* are insignificant and close to zero in in columns (1), (2), (5), and (6); the coefficients of *ISO* are significantly negative in columns (3) and (7), negative but insignificant in columns (4) and (8); in other words, with the consideration of dynamic and spatial spillover effects simultaneously, industrial structure

**Table 5** Dynamic spatial regressive results of the north sample

| Variables | *CS* (1) | *PC* (2) | *CS* (3) | *PC* (4) | *CS* (5) | *PC* (6) | *CS* (7) | *PC* (8) |
|---|---|---|---|---|---|---|---|---|
| *L.CS* | 0.544*** | | 0.563*** | | 0.539*** | | 0.581*** | |
| | (15.078) | | (14.512) | | (14.746) | | (13.580) | |
| *L.PC* | | 0.524*** | | 0.518*** | | 0.513*** | | 0.516*** |
| | | (13.532) | | (13.018) | | (13.123) | | (12.719) |
| *ISR* | −0.001** | −0.001*** | | | −0.001** | −0.001*** | | |
| | (−2.553) | (−2.970) | | | (−2.447) | (−2.793) | | |
| *ISO* | | | −0.271** | 0.037 | | | −0.572*** | 0.030 |
| | | | (−2.301) | (0.560) | | | (−3.034) | (0.403) |
| *FD* | | | | | 0.033 | 0.038 | 0.117** | 0.029 |
| | | | | | (0.740) | (0.812) | (2.304) | (0.578) |
| *ISR*FD* | | | | | −0.000 | −0.000 | | |
| | | | | | (−0.113) | (−0.436) | | |
| *ISO*FD* | | | | | | | −0.051 | 0.017 |
| | | | | | | | (−0.653) | (0.269) |
| $\rho$ | −0.122** | −0.031 | −0.289*** | −0.028 | −0.118** | −0.037 | −0.539*** | −0.031 |
| | (−2.488) | (−0.968) | (−2.649) | (−0.727) | (−2.387) | (−1.145) | (−3.346) | (−0.760) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 270 | 270 | 270 | 270 | 270 | 270 | 270 | 270 |
| *R*-squared | 0.003 | 0.602 | 0.016 | 0.616 | 0.003 | 0.531 | 0.000 | 0.582 |

*z*-statistics in parentheses; ***$p$<0.01, **$p$<0.05, *$p$<0.1

optimization has a negative impact on carbon emissions scale, while the impacts of industrial structure rationalization on carbon emissions (i.e., carbon emissions scale and per capita carbon emission) and the impact of industrial structure optimization on per capita carbon emission are relatively weak. For the interactive terms of the key independent variables and the moderating variable (i.e., *ISR*FD* and *ISO*FD*), all the coefficients of them are insignificant; in other words, with the consideration of dynamic and spatial spillover effects simultaneously, the moderating effect of financial development on the process of industrial structure transformation affecting carbon emissions (i.e., carbon emissions scale and per capita carbon emission) in China is not supported any longer. Therefore, for the whole sample, it is noted that the coexistence of the dynamic and spatial spillover effects of the dependent variable should not be ignored in the analysis.

## Regional heterogeneity analysis

In order to verify the regional heterogeneity impact of industrial structure transformation on carbon emissions (i.e., carbon emissions scale and per capita carbon emission) in China, this study has divided the research sample into two regions largely by the Qinling-Huaihe Line: north and south and conducted in the three types of econometric models. Obviously, compared with the estimation results based on the OLS model and the dynamic SYS-GMM model, the estimation result based on the dynamic spatial lag model obviously has a stronger explanation. Thus, the corresponding results for the north sample and the south sample are reported in Tables 5 and 6, respectively. Compared with the results in Table 4, several main findings can be drawn here.

For the estimation results of the north sample in Table 5, all the coefficients of *ISR* are significantly negative rather than insignificant and close to zero in columns (1), (2), (5), and (6); in other words, industrial structure rationalization has a direct negative impact on carbon emissions (i.e., carbon emissions scale and per capita carbon emission) in northern regions of China. In addition, the coefficients of *ISO* are also significantly negative in columns (3) and (7), negative but insignificant in columns (4) and (8); in other words, with the consideration of dynamic and spatial spillover effects simultaneously, industrial structure optimization has a negative impact on carbon emissions scale in the northern regions of China, while its impacts on per capita carbon emission in the northern regions of China is relatively weak. Moreover, all the four coefficients of the interactive terms of the key independent variables and the moderating variable (i.e., *ISR*FD* and *ISO*FD*) are

**Table 6** Dynamic spatial regressive results of the south sample

| Variables | *CS* (1) | *PC* (2) | *CS* (3) | *PC* (4) | *CS* (5) | *PC* (6) | *CS* (7) | *PC* (8) |
|---|---|---|---|---|---|---|---|---|
| *L.CS* | 0.368*** | | 0.332*** | | 0.315*** | | 0.313*** | |
| | (6.670) | | (6.274) | | (5.722) | | (5.691) | |
| *L.PC* | | 0.348*** | | 0.340*** | | 0.310*** | | 0.322*** |
| | | (6.410) | | (6.233) | | (5.657) | | (5.717) |
| *ISR* | 0.001 | 0.001 | | | 0.001* | 0.001* | | |
| | (1.619) | (1.349) | | | (1.924) | (1.832) | | |
| *ISO* | | | −0.088 | −0.000 | | | −0.100 | −0.035 |
| | | | (−1.144) | (−0.006) | | | (−1.283) | (−0.440) |
| *FD* | | | | | 0.072 | 0.076* | 0.052 | 0.082* |
| | | | | | (1.629) | (1.694) | (1.191) | (1.806) |
| *ISR*FD* | | | | | 0.005*** | 0.004** | | |
| | | | | | (2.660) | (2.358) | | |
| *ISO*FD* | | | | | | | −0.036 | 0.047 |
| | | | | | | | (−0.626) | (0.793) |
| $\rho$ | −0.094*** | −0.072*** | −0.060** | −0.097*** | −0.079*** | −0.065*** | −0.063** | −0.073*** |
| | (−3.444) | (−2.879) | (−2.077) | (−3.773) | (−2.910) | (−2.576) | (−2.080) | (−2.719) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 270 | 270 | 270 | 270 | 270 | 270 | 270 | 270 |
| *R*-squared | 0.104 | 0.593 | 0.381 | 0.445 | 0.122 | 0.612 | 0.339 | 0.583 |

*z*-statistics in parentheses; ***$p$<0.01, **$p$<0.05, *$p$<0.1

insignificant; in other words, with the consideration of dynamic and spatial spillover effects simultaneously, the moderating effect of financial development on the process of industrial structure transformation affecting carbon emissions (i.e., carbon emissions scale and per capita carbon emission) in the northern regions of China is also not supported. Last but not least, the dynamic and spatial spillover effects of the dependent variable are basically in line with the whole sample; in other words, the temporal inertia of carbon emissions has a positive impact on the current period of carbon emissions in the northern regions of China; the spatial spillover effect has to some extent reduced carbon emissions (i.e., carbon emissions scale and per capita carbon emission) in the northern regions of China, while this reduction effect on carbon emissions scale is obviously stronger than per capita carbon emission in the northern regions of China.

For the estimation results of the south sample in Table 5, the coefficients of *ISR* are significantly positive in columns (5) and (6), while in columns (1) and (2) are insignificant; in other words, only with the introduction of *ISR*FD*, the direct positive effect of industrial structure rationalization on carbon emissions (i.e., carbon emissions scale and per capita carbon emission) in the southern regions of China is conditionally established. However, all the coefficients of *ISO* are insignificant in columns (3), (4), (7), and (8); in other words, no matter with or without the introduction of *ISO*FD*, the direct positive effect of industrial structure optimization on carbon emissions (i.e., carbon emissions scale and per capita carbon emission) in the southern regions of China is not established. Moreover, all the coefficients of *ISR*FD* are significantly positive in columns (3) and (4), while the coefficients of *ISO*FD* are insignificant in columns (7) and (8); in other words, with the consideration of dynamic and spatial spillover effects simultaneously, financial development has positively moderated the nexus between industrial structure rationalization and carbon emissions in the southern regions of China, while the moderating effect of it on the process of industrial structure optimization affecting carbon emissions (i.e., carbon emissions scale and per capita carbon emission) is not established in the southern regions of China. Furthermore, the dynamic effects of the dependent variable are basically in line with the whole sample; in other words, the temporal inertia of carbon emissions (i.e., carbon emissions scale and per capita carbon emission) has a positive impact on the current period of it in the southern regions of China. Last but not least, all the spatial lag coefficients of the dependent variable are significantly negative; in other words, the spatial spillover effect of carbon emissions has to some extent reduced local carbon emissions (i.e., carbon emissions scale and per capita carbon emission) in the southern regions of China.

## Conclusions and policy recommendations

### Conclusions

To systematically investigate the impact of industrial structure transformation (industrial structure optimization and industrial structure rationalization) on carbon emissions (carbon emissions scale and per capita carbon emission) and the moderating effect of financial development in China at national and regional levels, this study comprehensively conducts an empirical study by using the OLS model, the dynamic SYS-GMM model, and the dynamic spatial lag model. A balanced panel dataset for 30 provinces in China covering the period 2000–2018 is analyzed. This study considers the dynamic and spatial spillover effects simultaneously; the main findings of this study are as follows:

(1) Industrial structure transformation (industrial structure optimization and industrial structure rationalization) does affect the carbon emissions (carbon emissions scale and per capita carbon emission). However, the moderating effect of financial development on the process of industrial structure transformation affecting carbon emissions in China is not supported. That may because both industrial structure transformation and carbon emissions have two key dimensions, the moderating effect of financial development may be different according to different scenarios. According to the relationship between industrial structure transformation, carbon emissions, and financial development, the main findings of this study can be divided into four scenarios as discussed below.

(2) On the one hand, the industrial structure optimization has a negative impact on both carbon emissions scale and per capita carbon emission, although its impact on the per capita carbon emission is weak. That means the industrial structure optimization is not beneficial for reducing the carbon emissions since the mismatched relationship between industrial structure and environmental-friendly demands. On the other hand, the impacts of industrial structure rationalization on both carbon emissions scale and per capita carbon emission are weak.

(3) Specifically, industrial structure optimization has a negative impact on both carbon emissions scale and per capita carbon emission in the northern regions of China, although its impact on the per capita carbon emission is relatively weak. In addition, industrial structure rationalization has a direct negative impact on both carbon emissions scale and per capita carbon emission in the northern regions of China.

(4) The direct positive effect of industrial structure rationalization on carbon emissions (carbon emissions scale and per capita carbon emission) in the southern regions of China is established after the introduction of *ISR*FD*. However, no matter with or without the introduction of *ISO*FD*, the direct positive effect of industrial structure optimization on carbon emissions (carbon emissions scale and per capita carbon emission) in the southern regions of China is not established. Moreover, financial development has positively moderated the nexus between industrial structure rationalization and carbon emissions (carbon emissions scale and per capita carbon emission) in the southern regions of China, while the moderating effect on the process of industrial structure optimization affecting carbon emissions (carbon emissions scale and per capita carbon emission) is not established in the southern regions of China.

(5) The temporal inertia of carbon emissions (carbon emissions scale and per capita carbon emission) has a positive impact on the current period of it in China, the northern regions of China, and the southern regions of China. In addition, the spatial spillover effect of carbon emissions has to some extent reduced local carbon emissions (carbon emissions scale and per capita carbon emission) in China, the northern regions of China, and the southern regions of China, while this reduction effect on carbon emissions scale is obviously stronger than per capita carbon emission in China and the northern regions of China.

### Policy recommendations

This study yields several implications for practice. For effectively reducing the carbon emissions, the following policy recommendations are proposed according to our research findings.

First, improving the performance of industrial structure transformation (industrial structure rationalization and industrial structure optimization) is imperative due to the unsatisfied impacts of industrial structure transformation on carbon emissions (i.e., carbon emissions scale and per capita carbon emission) such as popularizing advanced technology, strengthening environmental regulations, developing green production motivation. These not only benefits for improving the performance of industrial structure transformation, but also benefits for controlling greenhouse gas emissions and combating against global climate change.

Second, due to the insignificant impacts of industrial structure optimization on per capita carbon emission, and its insignificant spatial spillover effects on the northern regions of China, green consumption concept and green production mode should be conducted during the process of industrial structure optimization. Managers should pay more attention on the essential effect of green consumption and green production mode during the industrial structure optimization process and the policy-making progress. That provides a supportive environment for developing green consumption and green production mode gradually.

In addition, for strengthening the moderating effect of financial development on the process of industrial structure transformation affecting carbon emissions in China, specific financial reward and tax subsidy should be provided. That can accelerate the transformation of production process, accelerating the positive effect of industrial structure transformation industrial structure rationalization and industrial structure optimization) on carbon emissions (carbon emissions scale and per capita carbon emission) in China.

Finally, the standardized reward and punishment system should be established, implemented, and supervised in response to soften the temporal inertia and to enjoy the spatial spillover effect of carbon emissions (carbon emissions scale and per capita carbon emission). These measures benefit for providing conditions with constraints for enterprises to improve their production process and reduce the unnecessary carbon emissions. Furthermore, the standardized reward and punishment system can take the lead in achieving a great performance on reducing carbon emissions, as well as achieve a win-win scenario that includes both economic growth and sustainable development.

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**Author contribution** Yanchao Feng: Conceptualization, Methodology, Writing—Original draft; Hongyu Wu: Writing—Reviewing and Editing

**Data availability** The data used to support the findings of this study are available from the corresponding author upon request.

## Declarations

**Ethics approval and consent to participate** Not applicable.

**Consent for publication** Not applicable.

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