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Abstract

Tax policymaking in China has created conditions for local governments to strategically leverage tax policies (e.g., tax preferences, tax collection and management efficiency, and fiscal subsidies) to have carbon dioxide (CO_2) emissions peak before 2030 and carbon neutrality before 2060. By constructing an endogenous growth model with tax competition, capital mobility, technological innovation, and carbon emissions, this study investigates how tax competition is influencing firm-level behavior and providing climate-relevant policy implications. It has theoretically demonstrated that this effect depends on technological innovation and operates through the capital mechanism. This finding is empirically confirmed in this analysis using a spatial panel threshold model with fixed effects designed to fit a balanced provincial panel dataset in China over the period 2005–2018. The main results are fourfold. First, provinces with similar carbon emissions intensity (CEI) tend to cluster spatially. That is, a province with a high CEI usually has neighbors with high CEIs. Second, a threshold effect is confirmed, revealing that higher tax collection and management efficiency (lower tax competition) decreases CEI if technological innovation is below the threshold value; otherwise, lower tax competition usually increases CEI. Third, capital mobility is a potential mechanism through which tax competition influences CEI. Specifically, provinces with a high level of technological innovation attract more knowledge- and technology-intensive firms and crowd out firms with low innovation capacities, potentially reducing local CEI. Finally, as indicated in our spatial heterogeneity analysis, the effect of higher tax competition decreasing CEI is only observed in the western region. These findings suggest the need for cross-provincial collaboration in developing taxation policies to ensure these policies help to advance the transition to a low-carbon economy and raise capital entry barriers for high-carbon emission projects in provinces with a low level of technological innovation.

Key policy insights

- Cross-provincial taxation policies can be designed to encourage the transition to a low-carbon economy due to spatial agglomeration and heterogeneity of carbon emissions intensity (CEI).
- The focus of tax competition should be knowledge- and technology-intensive firms with a high level of technological innovation.
- Tax competition can be relaxed in China's provinces with a low level of technological innovation to reduce CEI; otherwise, it should be strengthened.
- The central government in China could usefully raise capital entry barriers for high-carbon emission projects in provinces with low levels of technological innovation and guide local governments to attract more projects with high returns and low carbon emissions to avoid a race to the bottom.

Keywords: Tax competition; CO_2 emissions intensity; Spatial panel threshold model; Technological innovation; Capital mobility

1. Introduction

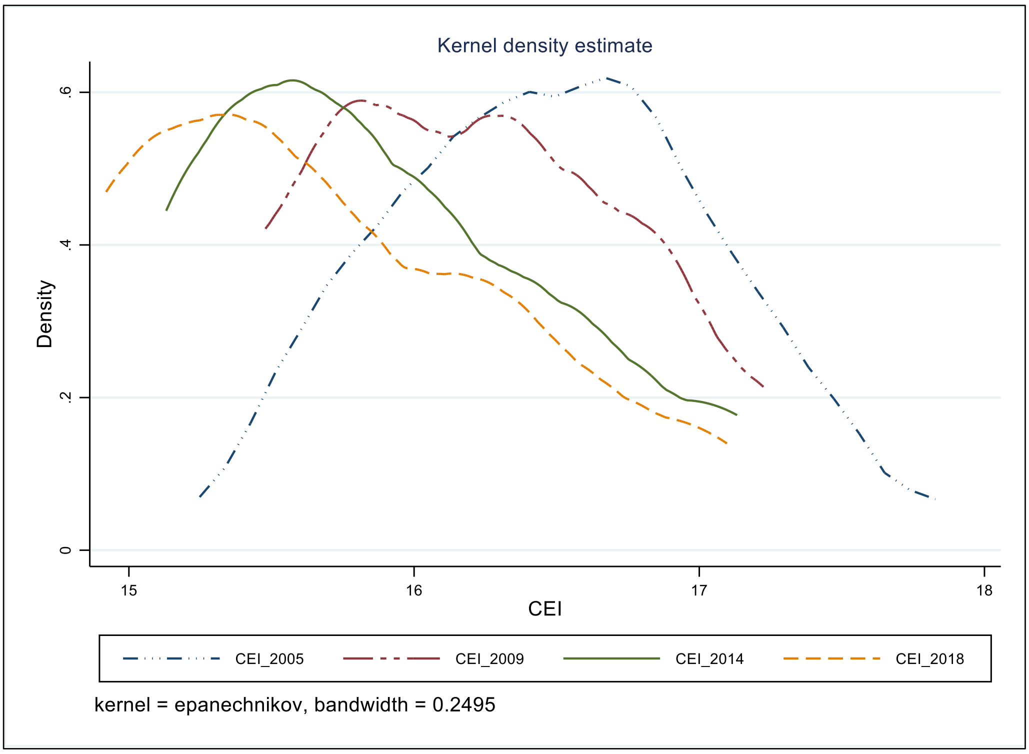
As one of the primary greenhouse gases, human-induced carbon dioxide (CO_2) emissions have risen tremendously since the Industrial Revolution, significantly contributing to global warming, extreme weather events, and human health risks. This hinders sustainable development of the world economy, as well as endangers human survival, driving worldwide endeavors to reduce CO_2 emissions. Along with the rapid industrialization and urbanization, China's economy has shown heavy reliance on coal consumption, a major source of CO_2 emissions, making it the largest CO_2 emitter in the world in 2006 (Global Carbon Budget, 2020) and responsible for 30.6% of the global CO_2 emissions in 2020 (Statistical Review of World Energy, 2021). Although China has gradually produced and consumed more clean energy in recent years, its coal consumption remains high at 57.7% of its total energy consumption in 2019 (China Statistical Yearbook, 2020). To achieve the proposed 2020 goals of reaching carbon peak by 2030 and carbon neutrality by 2060, there is an imminent need for an energy transition plan in China to guide its actions to rapidly transition from coal and petroleum to cleaner energy sources (IEA, 2021). Such a plan will undoubtedly generate a range of environmental, social, and economic benefits, but it also poses considerable challenges to China's economy, particularly in the short run (Fu and Geng, 2011; Ganda, 2019; Banerjee et al., 2020).

The dual goals of CO_2 emissions reduction and stable economic growth can possibly be managed more easily in China than elsewhere in part because of its fiscal decentralization. Under the law, local governments can independently determine fiscal revenues and expenditures to some extent (Zhang et al., 2011; Cheng et al., 2020; Khan et al., 2021). This flexibility enables local governments to use tax policies to compete for firms to move to their regions. For example, they use different tax preferences, tax collection and management efficiency, and fiscal subsidies as a form of regulatory competition to attract various types of firms with differing technology and carbon emissions (Xiao and Wu, 2020; Liu et al., 2020). In this study, this is what we refer to as "tax competition."

Theoretically, tax competition originates from economic integration, fostering relocation of productive resources such as capital, labor, and technology that is promoted by new transportation, communication, and information technologies (Banerjee et al., 2020). Empirically, the above correlations between tax competition and resource mobility, particularly capital mobility, are often examined using a non-cooperative game framework. As previously determined, governments are indifferent in the Nash equilibrium under non-preferential taxation, yielding the same tax rates for both countries and non-existence of capital flows across countries (Peralta and van Ypersele, 2005; Hristu-Varsakelis et al., 2011; Liesegang and Runkel, 2018). Additionally, China's market-oriented reforms attract huge inflows of foreign capital; combined with its official promotion system focusing heavily on local economic performance, these policies establish a basis for local governments to strategically leverage tax policy and tax competition (Hynes et al., 2022).

In China, provinces are commonly recognized as administrative divisions and we observe that provinces with high levels of technological innovation are more likely to use tax competition to attract more knowledge- and technology-intensive firms, leading to lower CO_2 emissions intensity (CEI). Conversely, provinces with low levels of technological innovation usually attract more energy- and labor-intensive firms that increase local CEIs (Scott, 2006; Wang et al., 2010). Such a phenomenon indicates a potential threshold effect of tax competition on CEI, which describes a process by which the relationship between tax competition and CEI changes significantly as the level of technological innovation exceeds some critical value. Meanwhile, unbalanced provincial economic development, in terms of resource endowment, comparative industrial advantages, and emissions reduction costs, indicates the potential spatial heterogeneity of CEI (Pi et al., 2010; Lemoine et al., 2015; He et al., 2018; Zhao et al., 2019).

To provide an overview of the historical and current circumstances of CEI and tax competition in China, Figure 1 presents their provincial density curves in the selected years to illustrate distributions over the period 2005–2018. As observed, the CEI curves shifted to the left, implying a decrease in the overall CEI in China, whereas these curves became less spread, indicating a decrease in provincial CEI disparities. However, the density curves for tax competition shifted to the right, with the length of right tails becoming increasingly longer in the selected years. This indicates that the overall tax competition in China became more intense, and provincial disparities expanded over the period 2005–2018.



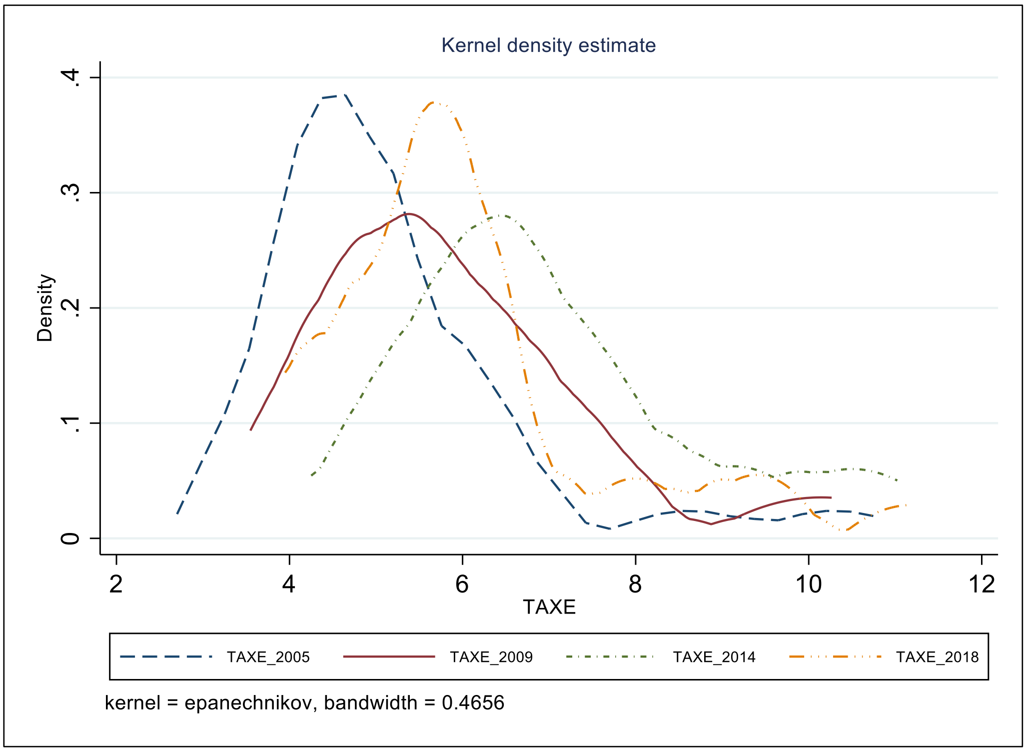


Figure 1 Kernel density curves of CEI and tax competition

Note: The kernel density estimation is a mathematical process of finding an estimated probability density function of a random variable. The estimation attempts to infer characteristics of a population based on a finite data set, enabling one to create a smooth curve given a set of random data.

Regrettably, the existing literature has primarily focused on the impact of tax competition on environmental quality (e.g., discharged wastewater, waste gas, and solid waste) with inconsistent findings. Some argue that tax competition increases aggregate pollutants by lowering consumer prices for polluting goods or reducing public expenditure (Cremer and Gahvari, 2004; Pi et al., 2014), while others argue that tax competition decreases pollutants by helping local governments obtain more funds for pollutants reduction investments (Holzinger and Sommerer, 2011). Insufficient attention has been paid to the potential threshold effect, capital mobility mechanism, and spatial heterogeneity of tax competition on CEI in China. To address this limitation, we theoretically demonstrate and empirically confirm that the impact of tax competition on CEI depends on the level of technological innovation; that it exhibits spatial heterogeneity; and that it transmits through the capital mechanism. Consequently, this study contributes to the field in three aspects. First, an endogenous growth model with tax competition, capital mobility, technological innovation, and carbon emissions contributes to the threshold effect analysis of tax competition on CEI from a theoretical perspective. Second, using a balanced provincial panel dataset in China over the period 2005–2018, a spatial panel threshold model with fixed effects is constructed to confirm the presence of spatial heterogeneity, demonstrating superior model applicability and effectiveness. Third, the essential role of capital mobility in mediating the impact of tax competition on CEI contributes to the strategic application of policymaking, presenting the opportunity for using tax competition as a policy tool to accelerate the transition to a low-carbon economy through promoting technological innovation.

The remainder of this study is structured as follows. We first provide a multisector endogenous growth model for theoretical analysis and a spatial panel threshold model with fixed effects for empirical analysis. We then analyze the main findings. We conclude by discussing the climate policy relevant implications and provide avenues for future research.

2. Literature review

2.1 Determinants of carbon emissions

As carbon emissions receive increasing attention worldwide, tremendous efforts have been made to identify their determinants. Considering the superiority of the stochastic impacts by regression on population, affluence and technology (STIRPAT) model in incorporating additional variables, previous studies have applied this model extensively, identifying economic development, population, and technology as the three fundamental determinants of CO_2 emissions (Dietz and Rosa, 1997; Shahbaz et al.,2016; Yang et al., 2018; Li et al.,2019). In general, rapid economic development and large population indicate more production and consumption activities, leading to increased resource consumption and CO_2 emissions (Shuai et al., 2017; Zhu et al., 2018). Technology is generally expected to decrease carbon emissions based on its role in promoting the use of cleaner energy, installing green equipment, and advancing production processes (Dong et al., 2018; Ganda, 2019).

To produce evidence for the strategic development of appropriate carbon emissions reduction policies, existing literature has also identified a variety of additional determinants to deepen the understanding of how human activities affect carbon emissions. The most frequently identified determinants include urbanization (Sun and Huang, 2020; Gao et al., 2021), education (Zhu et al.,2021; Sarwar et al., 2021), industrial structure (Zhao et al., 2018), foreign direct investment (FDI; Shahbaz et al., 2019; Mukhtarov et al., 2021), energy consumption (Waheed et al., 2019), and forest coverage (Waheed et al., 2018). Previous findings have indicated that the rapid urbanization process, high share of coal and petroleum consumption, and high share of the secondary industry increase carbon emissions, while high levels of education and forest coverage are expected to decrease carbon emissions. However, there are mixed findings regarding the impact of FDI. Some researchers assert the role of FDI in reducing carbon emissions due to technology spillovers (Yu and Xu, 2019), whereas others argue that FDI expands production activities, resulting in increased carbon emissions (Shahbaz et al., 2019). Despite the profound implications of the above determinants, few studies have focused on tax competition and the potential capital mobility mechanism, which will be reviewed below.

2.2 Tax competition and environmental quality

The challenge of maintaining economic growth while enhancing environmental quality has always been a critical concern for governments' tax policymaking and requires considerable attention to examine how tax competition can more strategically achieve environmental goals given an appropriate rate of economic growth. Although tax competition theoretically instigates capital mobility, attracts different types of firms, and influences local environmental quality, inconsistent empirical evidence has been provided in existing studies. Some studies have argued that tax competition tends to diminish environmental quality. For example, Cremer and Gahvari (2004) asserted that environmental quality deterioration usually occurs if emissions tax rate is below the unlimited Nash equilibrium due to firms' preferences for high-polluting technologies. Using a differentiated oligopoly with a partially public firm and an entirely private firm, numerical simulations by Pal and Saha (2015) indicated that the public firm's concern for the environment may cause a lower tax rate but higher environmental damage. From the financial stress perspective, Bai et al. (2019) found that tax competition can negatively influence the local and neighboring environment, causing severe environmental pollution, and making environmental quality below the socially optimal level. In addition, vicious tax competition across regions from lowering tax rates has been found to reduce local governments' tax revenues, weaken capacities for supplying public goods and services, and cause increased environmental degradation (Li and Zhao, 2017). Wen (2013) and Bai et al. (2019) also demonstrated that tax competition aggravates environmental pollution.

In contrast, some previous studies have argued that tax competition can improve environmental quality. For example, Zhang et al. (2015) found that tax competition enhances environmental problems of solid waste. He et al. (2016) demonstrated that the impact of tax competition on environmental pollution exhibits regional disparities. Eichner and Pethig (2018) considered an economy with two asymmetric jurisdictions, discovering that capital tax competition improves local pollution but exacerbates capital distortion. It has also been widely recognized that government competition caused by fiscal decentralization reduces pollution discharge, as it gives local governments more incentives to mitigate environmental pollution within their jurisdiction (Millimet, 2003; Tan et al., 2015).

2.3 Research models

To quantify the impacts of the identified determinants on carbon emissions, a range of econometric models have been applied to investigate various datasets. For example, the Granger causality test and vector error correction model (Shahbaz et al., 2016), principal component analysis (Yang et al.,2018) and linear autoregressive distributed lag (Haug and Ucal, 2019) are often used to examine time series data. Considering the advantages of panel data in controlling heterogeneity, obtaining unbiased estimation, and improving collinearity, various techniques have been proposed to examine panel datasets, predominantly including structural decomposition analysis (Dong et al., 2018), the generalized method of moments (Shahbaz et al., 2019), panel cointegration estimation (Shuai et al., 2017), stochastic frontier analysis (Sun and Huang, 2020), and the network approach (Gao et al., 2021). To further capture different characteristics in panel data, the standard panel data regression model has been extended to constant and time-varying coefficient (Mukhtarov et al., 2021), fixed- and random-effects (Khan & Ahmad,2021), dynamic (Zhu et al., 2021), and quantile regression panel data models (Dong et al., 2018). As the field of spatial econometrics progresses, the spatial lag regression (Davies and Naughton, 2014), spatial error model (Li and Mao, 2019) and spatial Durbin model (Hong et al., 2020) have been frequently used to examine how tax competition influences environmental quality. Bai et al. (2019) make a comprehensive comparison among these spatial models.

2.4 Research gaps

A thorough review of the existing research on tax competition and carbon emissions indicates the following three gaps to be filled in this study. First, apart from the previously identified determinants of carbon emissions, we identify tax competition and technological innovation as the key determinant and the threshold variable, respectively, examining how tax competition affects CEI. To this end, we construct an endogenous growth model to theoretically demonstrate the existence of a threshold effect of tax competition on CEI. Second, the mechanism through which tax competition influences CEI has not been well researched in previous studies. This study overcomes this gap by investigating if and to what extent the impact of tax competition on CEI is mediated through capital mobility. Third, using a spatial panel threshold model with fixed effects to capture the spatial heterogeneity of CEI in China, this study enriches the existing literature on the role of tax competition in influencing environmental quality as well as providing valid empirical insights for strategic cross-provincial emissions reduction policymaking.

3. Theoretical analysis: A multisector endogenous growth model

In this section, we construct an endogenous growth model with tax competition, capital mobility, technological innovation, and CO_2 emissions to explore the threshold effect and influential mechanism of tax competition on CEI. Assume that capital is the only mobile factor and the total amount of capital available for investment is k. The economy contains two adjacent provinces, A and B, competing for capital investment through tax competition. Under perfect competition, capital can flow freely between provinces A and B.

Government

Assume that the local government endeavors to attract capital inflow from its competitor through reducing taxes. Tax competition π_A and π_B indicate the level of tax reduction effort in provinces A and B, respectively. Given π_A and π_B, $p\left(\pi_A \mid \pi_B\right)$ represents the probability that province A will successfully attract capital inflow, which is assumed to increase in π_A and decrease in π_B. According to Basinger and Hallerberg (2004), the stochastic component of province A's rate of return follows the type I extreme-value distribution (i.e., the log Weibull distribution), which can be specified as follows:

$$p\left(\pi_A \mid \pi_B\right) = \frac{1}{1+e^{\pi_B - \pi_A}} \tag{1}$$

Then, the expected value of capital inflow to province A is as follows:

$$K = p\left(\pi_A \mid \pi_B\right) \cdot k = \frac{1}{1+e^{\pi_B - \pi_A}} \cdot k \tag{2}$$

Firm

There are two types of firms in the economy, including a research and development (R&D) sector that produces new knowledge and a goods sector that produces final output. The production of new knowledge has commonly been believed to depend on the number of R&D employees (L_Λ) as well as the existing knowledge stock (Λ), with the following knowledge production function (Romer, 1990; Abdih and Joutz, 2006).

$$\dot{\Lambda} = \delta L_\Lambda \Lambda \tag{3}$$

where $\dot{\Lambda}$ represents the flow of new knowledge produced in the economy and δ represents the productivity in the R&D sector. Financial constraints are usually observed in this sector. As asserted by Romer (1990), R&D labor cost is not higher than the marginal revenue product if there is no distortion in financial markets; however, financial markets are incomplete, indicating that a high level of financial development tends to reduce the cost of financing R&D and attract more investment. As a result, the budget constraint facing the R&D sector is given by the following:

$$wL_\Lambda = \theta P_\Lambda \dot{\Lambda} \tag{4}$$

where w represents the unit wage for R&D employees. $\theta \in \left(0,1\right]$ measures the level of financial development and P_Λ denotes the market price of knowledge.

In contrast, the goods sector employs capital (K), labor, and knowledge to produce final output. Given the total amount of labor (L_Y) available in the economy, the goods production function is given by the following (Romer, 1990):

$$Y = \Lambda L_Y^\alpha K^{1-\alpha} \tag{5}$$

CO_2 emissions

As previously noted, China's rapid economic growth in the past decades has relied heavily on coal and oil consumption, making it a significant factor of CO_2 emissions (Xu et al., 2018; Rahman et al., 2020). Meanwhile, a negative elasticity of CO_2 emissions with respect to technological innovation is commonly observed (Fernández et al., 2018; Wang et al., 2019). Accordingly, Equation (6) is considered to capture how CO_2 emissions grow (Sukono et al., 2019;

Oryani, 2021).

$$\dot{P} = \Omega \mathrm{F}(\mathrm{Y}, \Lambda) \tag{6}$$

where $\dot{P}$ represents the increase in CO_2 emissions and Ω represents the economic growth rate. To address the observed impacts of economic growth (Y) and technological innovation (Λ) on CO_2 emissions in China, we adopt the Cobb-Douglas production function $\mathrm{F}(\mathrm{Y}, \Lambda) = \mathrm{Y}^{\omega} \Lambda^{-\varphi}$, with $\omega > 0$, $\varphi > 0$, and $\omega = \varphi + 1$.

Social welfare

Assume that society prefers both higher consumption (C) and lower CO_2 emissions (P). This indicates that social welfare is positively affected by consumption and negatively affected by CO_2 emissions, yielding the following instantaneous utility function.

$$U = \ln C - \beta \ln P \tag{7}$$

where $\beta > 0$ measures the strength of the impact of CO_2 emissions on social utility and P is assumed to be exogenous.

Social planning problem

The social planner aims to maximize the whole society's welfare in an infinite horizon economy, which can be formulated as the following problem:

$$\max \int_0^{\infty} (\ln C - \beta \ln P) e^{-\rho t} dt$$

$$s.t. \begin{cases} \dot{P} = \Omega \mathrm{Y}^{\omega} \Lambda^{-\varphi} = \Omega \Lambda L_Y^{\alpha\omega} K^{(1-\alpha)\omega} \\ \dot{K} = Y - C = \Lambda L_Y^{\alpha} K^{1-\alpha} - C \end{cases} \tag{8}$$

where Λ and C are control variables, while P and K are state variables. By solving this problem (see Appendix 1), *P* can be expressed as:

$$P = \frac{\beta C \Omega L_Y^{\alpha\varphi} K^{\omega - \alpha\omega + \alpha}}{(1-\alpha)\left(\frac{Y}{\Lambda} - \frac{\omega Y}{\Omega} + \varphi\right)} \tag{9}$$

Since CEI represents CO_2 emissions per unit of output in the economy, it is written as:

$$E = \frac{P}{Y} = \frac{\beta C \Omega L_Y^{\alpha\varphi} K^{\omega - \alpha\omega + \alpha}}{(1-\alpha)\left(\frac{Y^2}{\Lambda} - \frac{\omega Y^2}{\Omega} + \varphi Y\right)} \tag{10}$$

Taking the partial derivative of Equation (10) with respect to π_A, the evolution of E is:

$$\dot{E}(\pi_A)=\frac{\beta C L_Y^{\alpha\varphi+1}\Lambda K^{\omega-\alpha\omega}\left[(\omega-\alpha\omega+\alpha)\left(\Omega L^{\alpha}K^{1-\alpha}-\omega\Lambda L^{\alpha}K^{1-\alpha}+\Omega\varphi\right)+2(1-\alpha)L^{\alpha}K^{1-\alpha}(1-\Omega)-(1-\alpha)\varphi\right]}{(1-\alpha)^3\left(\Lambda L_Y^{2\alpha}K^{2(1-\alpha)}-\frac{\omega\Lambda^2 L_Y^{2\alpha}K^{2(1-\alpha)}}{\Omega}+\varphi\right)^2}\cdot\dot{K}(\pi_A) \tag{11}$$

Assume $\Psi=(\omega-\alpha\omega+\alpha)\left(\Omega L^{\alpha}K^{1-\alpha}-\omega\Lambda L^{\alpha}K^{1-\alpha}+\Omega\varphi\right)+2(1-\alpha)L^{\alpha}K^{1-\alpha}(1-\Omega)-(1-\alpha)\varphi$ in Equation (11). It can be concluded that $\dot{E}(\pi_A)$ is affected by $\dot{K}(\pi_A)$ if $\Psi\neq 0$. As a result, the following hypothesis is proposed.

H1: Capital mobility is a significant mechanism through which tax competition affects CEI.

As previously noted, tax competition can generate cross-provincial movement of capital resources from a province with a low return on capital to a province with a high return on capital. This encourages profit-maximizing, tax-paying firms to leverage the exit strategy to force local governments to compete for taxable assets and activities, potentially reducing these firms' fiscal burdens (Genschel and Schwarz, 2011). However, Janeba (1995) asserted that the allocation of capital stock in the non-cooperative Nash equilibrium is inefficient, motivating both countries to seek cooperative taxation (e.g., credit, exemption, and deduction methods) to improve welfare. For profit-maximizing, tax-paying firms, the choice between different types of taxation depends on the costs of moving capital resources across provinces and the tax incentives received from provinces with potential capital inflow (Mongrain and Wilson, 2018). Provinces with different tax policies usually attract different types of capital inflow. As a result, if more high pollution and high energy consumption firms are attracted by tax competition (e.g., low capital entry barriers, fiscal subsidies), a higher local CEI tends to be observed. In contrast, a lower CEI is more likely to be observed if tax competition attracts more low pollution and low energy consumption firms.

By taking the partial derivative of Equation (2) with respect to π_A, the capital growth function can be expressed as $\dot{K}(\pi_A)=\frac{e^{\pi_B-\pi_A}}{\left(1+e^{\pi_B-\pi_A}\right)^2}\cdot k>0$. With $\omega-\alpha\omega+\alpha>\alpha$, we find $\frac{\varphi}{(\omega-\alpha\omega+\alpha)K^{1-\alpha}L^{\alpha}}>0$ and $\frac{(1-\alpha)(1-\Omega)}{(\omega-\alpha\omega+\alpha)\Omega}>0$. Accordingly, it can be concluded that the sign of $\dot{E}(\pi_i)$ depends on the magnitude of Ψ in Equation (11). If $\Psi>0$, we find $\dot{E}(\pi_A)>0$, implying that CEI rises as tax competition increases. In contrast, if $\Psi<0$, we find $\dot{E}(\pi_A)<0$, implying that CEI tends to decrease as tax competition increases. As a result, the following hypothesis is proposed.

H2: The existence of a threshold effect indicates that tax competition positively affects CEI when technological innovation is below the threshold value; otherwise, they are negatively related.

This indicates the presence of a threshold effect on CEI from tax competition, which is primarily due to the role of the existing technology stock (Λ). In practice, provinces with high levels of technological innovation are more likely to attract more knowledge- and technology-intensive service firms that consume fewer fossil fuels and enjoy higher emissions reduction, potentially reducing local CEI. These firms are also more likely to engage in technological reform and innovation and develop new technologies in a more time-efficient and cost-efficient manner (Grossman and Helpman,1994). Economies of scale also indicate that unit production costs decrease as the level of technology increases (Qiu and Anadon, 2012). This motivates firms with high technology demands to take advantage of tax competition in provinces with high levels of technological innovation, which engenders higher awareness of emissions reduction and capacities, contributing to lower CEI (Guerrero et al., 2018). As an exogenous threshold variable, technological innovation depends largely on local capital accumulation, leading to innovation clusters in practice. Then, it is observed that provinces with low levels of technological innovation are more likely to attract energy- and labor-intensive industrial firms that consume more fossil fuels and have lower emissions reduction capacities, tending to increase local CEI (Liu et al., 2020). This suggests that appropriate tax competition policies (e.g., raising capital entry barriers) for high-carbon emission projects should be implemented in these provinces to reduce local CEIs.

4. Empirical analysis: A spatial panel threshold model with fixed effects

4.1 Determinant identification under the STIRPAT framework

Using the STIRPAT framework and referring to previous findings, we identify ten determinants affecting CEI in China. They are tax competition, the factor of interest, the three fundamental determinants (population, economic development, and technology) suggested in the STIRPAT framework, and six additional determinants of urbanization, education, industrial structure, FDI, energy consumption, and forest coverage that are commonly used in the existing literature. A summary of the identified determinants is presented in Appendix 2.

To quantify the impact of determinants on CEI, we logarithmically extend the original STIRPAT framework in Equation (12) to Equation (13), incorporating additional determinants.

$$I = aP^b A^c T^d e \tag{12}$$

$$\begin{aligned} \ln CEI = \beta_0 + \beta_1 \ln TAXE + \beta_2 \ln POP + \beta_3 \ln PGDP + \beta_4 \ln TEC + \beta_5 \ln URB \\ + \beta_6 \ln EDU + \beta_7 \ln INS + \beta_8 \ln RFDI + \beta_9 \ln TCG + \beta_{10} \ln FOREST + \varepsilon \end{aligned} \tag{13}$$

where I and e in Equation (12) represent CEI in this study, and the corresponding error terms. P (population), A (economic development), and T (technology) are the three fundamental determinants. a,b,c,d are parameters to be estimated. β_0 and ε in Equation (13) denote the constant and the error term, respectively. The impact of the identified determinant on CEI is measured by $\beta_k (k = 1,\cdots,10)$.

4.2 Data sources and descriptive statistics

As summarized in Appendix 2, $\ln CEI$ is the dependent variable and can be measured by the ratio of CO_2 emissions from energy consumption to gross domestic product (GDP). Due to the significant role of fossil fuels in emitting CO_2, we reference Wang et al. (2020) in Equation (14) to calculate CO_2 emissions from energy consumption.

$$E_{it} = \sum_{j=1}^{9} E_{it}^{j} b^{j} \theta^{j} \tag{14}$$

where E_{it}^{j} represents province i's consumption of energy j in year t, $j = 1, \cdots, 9$ indicates nine primary types of energies in China, b^{j} denotes the conversion coefficient between energy j and standard coal, and θ^{j} represents the carbon emission coefficient of energy j.

Tax competition is the factor of interest, which is represented by ($\ln TAXE$) and measured by the ratio of the actual tax revenue ($taxg$) to tax capacity ($Taxg$; Mkandawire, 2010), indicating that intense tax competition usually reduces $\ln TAXE$. Nevertheless, $Taxg$ is unobservable but can be indirectly measured by the regression model which is shown in Appendix 3.

Additionally, we measure technology ($\ln TEC$) by the number of local patents granted and capital ($\ln CAP$) measured by self-raised funds[1] as threshold and the mediating variables, respectively (Fu and Geng, 2011). More details regarding other control variables are presented in Appendix 2. A balanced panel dataset of 30 Chinese mainland provinces, autonomous regions, and municipalities[2] over the period 2005–2018 was collected from the China Statistical Yearbook, the China Energy Statistical Yearbook, the China Taxation Yearbook, the Finance Yearbook of China, and Intergovernmental Panel on Climate Change (https://www.ipcc.ch/) and National Bureau of Statistics (http://www.stats.gov.cn/) websites, yielding 480 observations. To obtain the real values of $\ln CEI$, $\ln CAP$, and $\ln PGDP$, comparable prices in 2005 are used to eliminate the inflation effect. Table 1 presents the descriptive statistics of the identified factors.

1 According to China Statistical Yearbook, self-raised funds can be defined as "funds for investment in fixed assets received during the reference period by investing units, including self-owned funds owned by various enterprises and institutions and funds raised from other units, excluding financial funds, funds borrowed from financial institutions and overseas funds."

2 Due to data availability, Hong Kong, Macau, Taiwan, and Tibet are not included in this study.

Table 1 Descriptive statistics of determinants

Variable	Mean	Standard deviation	Minimum	Maximum
$\ln CEI$	16.06	0.63	14.91	17.57
$\ln TAXE$	1.83	0.31	1.15	2.99
$\ln TEC$	9.92	1.61	5.37	13.58
$\ln CAP$	8.47	1.13	4.96	10.63
$\ln POP$	8.17	0.74	6.29	9.33
$\ln PGDP$	10.36	0.63	8.55	11.93
$\ln TEC$	9.92	1.61	5.37	13.58
$\ln URB$	3.94	0.25	3.29	4.49
$\ln EDU$	2.61	0.23	1.57	3.10
$\ln INS$	3.75	0.22	2.80	4.12
$\ln RFDI$	7.92	0.85	6.16	10.96
$\ln TCG$	20.26	1.28	16.74	23.51
$\ln FOREST$	7.89	0.72	5.99	8.80

4.3 Spatial panel threshold model with fixed effects

As widely accepted, Moran's *I* (see Appendix 4), the Lagrange multiplier (LM), and robust LM tests provide the basis for selecting appropriate spatial models which is found to be a spatial panel threshold model with fixed effects in this study to validate the hypotheses concerning the threshold effect of tax competition on CEI. According to Hansen (1999) and Lee and Yu (2010), the model can be expressed as follows:

$$\ln CEI_{it} = \rho \cdot W \cdot \ln CEI_{it} + \ln TAXE_{it} \cdot \mathrm{I}\left(\ln TEC_{it} < \gamma\right) \cdot \beta_{11} + \ln TAXE_{it} \cdot \mathrm{I}\left(\ln TEC_{it} > \gamma\right) \cdot \beta_{12} + \mathbf{control}' \cdot \Theta + u_i + \varepsilon_{it} \tag{15}$$

where ρ represents the spatial correlation coefficient, W is the spatial weight matrix, $\ln TEC$ represents the threshold variable with the unknown threshold value γ, and **control** denotes the control factors of CEI identified in this study. $\mathrm{I}(\bullet)$ is an indicator function that equals 1 if the threshold condition is satisfied; otherwise, it is 0. u denotes the individual fixed effects, and ε is the corresponding error term. β_{11}, β_{12}, and Θ are parameters to be estimated. Other variables are defined as above. We can estimate the above parameters using the maximum likelihood estimation method and the particle swarm optimization algorithm (Hansen, 1999; Lee and Yu, 2010). The bootstrap self-sampling method is also used to obtain the asymptotic distributions of parameters and to test statistical significance (Efron, 1992). In addition, the validation of the capital mechanism and the construction of the spatial weight matrix are presented in Appendix 5.

5. Empirical results

5.1 Spatial dependence of CEI

The global Moran's *I*s of CEI in China over 2005–2018 are calculated and reported in Table 2. As observed, significant and positive Moran's *I* ranging from 0.334 in 2005 to 0.464 in 2010 indicates a positive spatial dependence of CEI. The local Moran's *I* of CEI are presented in Figure 2 for the years 2005, 2009, 2014, and 2018, wherein the vertical axis indicates the spatially-lagged CEI, the horizontal axis indicates the original CEI, and the slope of the fitted line represents the corresponding Moran's *I*. Most provinces are in the first and third quadrants in the selected years, demonstrating patterns of high–high or low–low clusters. As shown in Table 3, all tests except the robust LM test for spatial error effect are significant. These findings confirm the presence of positive spatial dependence of CEI in China, further motivating our consideration of the spatial effect of CEI.

Table 2 Values of Moran's *I*

Year	Moran's *I*	p-value	Year	Moran's *I*	p-value
2005	0.334***	0.000	2012	0.392***	0.000
2006	0.422***	0.000	2013	0.384***	0.000
2007	0.413***	0.000	2014	0.384***	0.000
2008	0.450***	0.000	2015	0.362***	0.000
2009	0.433***	0.000	2016	0.361***	0.000
2010	0.464***	0.000	2017	0.373***	0.000
2011	0.401***	0.000	2018	0.353***	0.000

Note: *** indicates statistical significance at 1% level.

Table 3 Results of Lagrange multiplier tests for spatial effect

Test	Statistic	p-value
Spatial Error:		
Moran's I	4.528	0.000
Lagrange Multiplier	17.147	0.000
Robust Lagrange Multiplier	1.452	0.228
Spatial Lag:		
Lagrange Multiplier	49.505	0.000
Robust Lagrange Multiplier	33.810	0.000

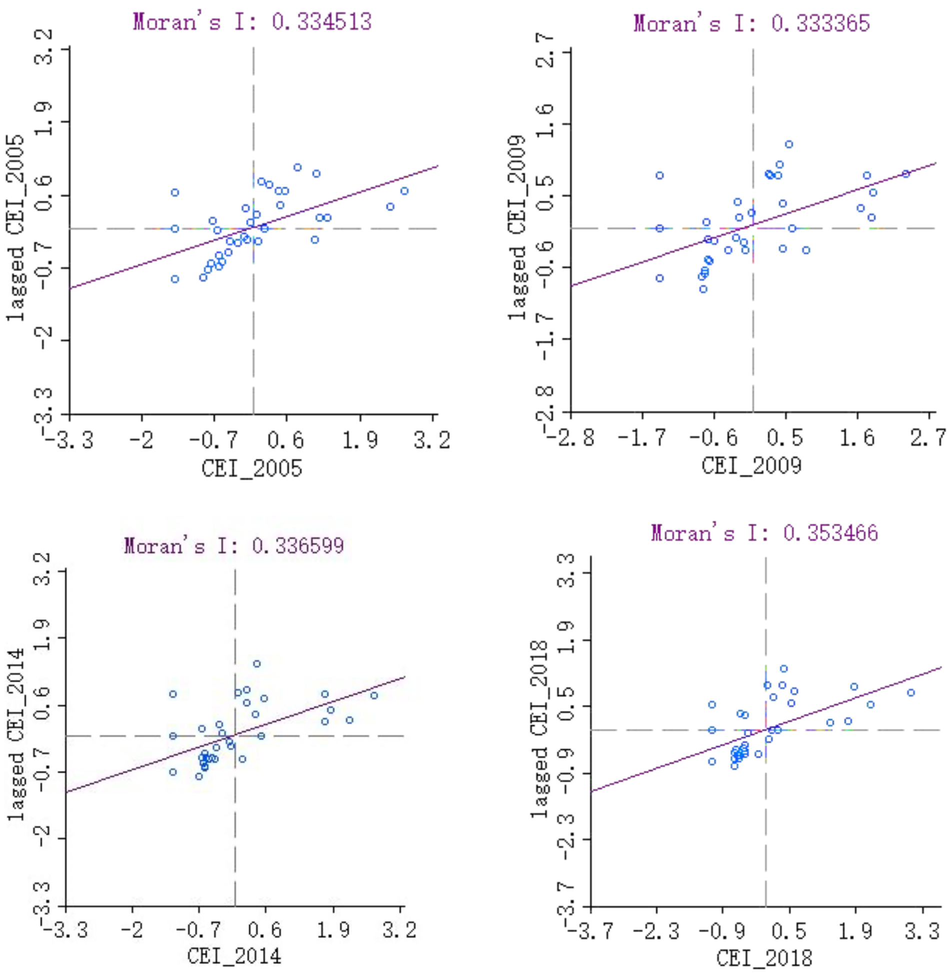


Figure 2 Moran's *I* scatter diagrams of CEI in the selected years

5.2 Results of threshold effect analysis

To establish a benchmark for validating the threshold effect of tax competition on CEI, a spatial lag model (Model 1) and Equation (13) without consideration of spatial effect (Model 2) are estimated and presented in Columns 2 and 3 in Table 4. Equation (15) with consideration of spatial effect is also estimated using the binary contiguity weights (Model 3), 700km-distance weights (Model 4), and 800km-distance weights (Model 5), as presented in Columns 4, 5, and 6, respectively. The spatial panel threshold model with fixed effects fits the dataset better, increasing the R^2 from 0.977 for Model 1 and 0.8904 for Model 2 to 0.9944 for Model 3, 0.9946 for Model 4, and 0.9944 for Model 5. This indicates that more than 99% of variations in CEI can be explained by the spatial panel threshold model with fixed effects. The significant and positive ρ further confirms the presence of the positive spatial dependence of CEI, which is 0.124 for Model 3, 0.125 for Model 4, and 0.122 for Model 5, respectively. However, the variable of interest $\ln TAXE$ shows an insignificant impact on CEI in Model 1, implying that the spatial lag model cannot capture the potential threshold effect.

Table 4 Estimation results of threshold effect

Variable	$\ln CEI$ (Model 1)	$\ln CEI$ (Model 2)	$\ln CEI$ (Model 3)	$\ln CEI$ (Model 4)	$\ln CEI$ (Model 5)
ρ	0.397***		0.124***	0.125***	0.122***
	(0.123)		(0.0217)	(0.0209)	(0.0209)
$\ln TAXE$ (0)	0.0362	-0.0546*	-0.0766***	-0.0379*	-0.0403*
	(0.0236)	(0.0325)	(0.0274)	(0.0289)	(0.0301)
$\ln TAXE$ (1)		0.0603***	0.0881***	0.073***	0.0719***
		(0.0229)	(0.0208)	(0.0203)	(0.0193)
Threshold value $\ln TEC$		6.4003***	6.41**	6.44**	6.42***
		(0.000)	(2.95)	(2.84)	(2.72)
$\ln POP$	0.350	0.215	0.0363	0.0345	0.0505
	(0.326)	(0.172)	(0.152)	(0.158)	(0.166)
$\ln PGDP$	-0.462***	-0.641***	-0.607***	-0.588***	-0.587***
	(0.124)	(0.0478)	(0.0426)	(0.046)	(0.0444)
$\ln TEC$	0.0661*	0.0719***	0.0504***	0.0634***	0.0644***
	(0.0359)	(0.0214)	(0.0197)	(0.0183)	(0.0197)
$\ln URB$	-0.132	-0.270*	-0.32**	-0.393***	-0.435***
	(0.402)	(0.158)	(0.144)	(0.146)	(0.141)
$\ln EDU$	0.107	0.0497	0.0731*	0.0331	0.0405
	(0.110)	(0.0522)	(0.0491)	(0.0499)	(0.0452)
$\ln INS$	0.116	0.219***	0.241***	0.184***	0.189***
	(0.136)	(0.0684)	(0.0583)	(0.0598)	(0.066)
$\ln RFDI$	-0.0388	-0.0493***	-0.0296**	-0.0407***	-0.0405***
	(0.0296)	(0.0185)	(0.0159)	(0.0173)	(0.0173)
$\ln TCG$	-0.00877*	7.74e-07	0.00162	-0.0119**	-0.012**
	(0.00486)	(5.49e-07)	(0.00545)	(0.00518)	(0.0054)
$\ln FOREST$	0.000323	0.00755	0.178**	0.0304	0.0363
	(0.0977)	(0.0922)	(0.0857)	(0.0904)	(0.0846)
N	30	30	30	30	30
T	14	14	14	14	14
Individual effect	Controlled	Controlled	Controlled	Controlled	Controlled
R^2	0.9770	0.8904	0.9944	0.9946	0.9944

Notes: Standard errors are included in parentheses. Model 1 is estimated without consideration of spatial effect. The binary contiguity weights, 700km-distance weights, and 800km-distance weights are used to estimate Models 2, 3 and 4, respectively. ***, ** and * indicate statistical significance at 1%, 5% and 10% level, respectively.

Examining Models 3-5 reveals consistent evidence regarding the threshold effect of tax competition on CEI. More specifically, the threshold values of $\ln TEC$ are found to be 6.41 for Model 3, 6.44 for Model 4, and 6.42 for Model 5, which are significant and similar in magnitude. Given that $\ln TEC$ is below the threshold value, significant and negative $\ln TAXE(0)$ across models imply that higher tax collection and management efficiency (lower tax competition) can significantly decrease CEI. In contrast, $\ln TAXE(1)$ consistently increases CEI in all models if $\ln TEC$ is above the threshold value, suggesting that higher tax collection and management efficiency (lower tax competition) can increase CEI. Taking Model 3 as an example, a 1% increase in tax collection and management efficiency (a 1% decrease in tax competition) brings a 0.0766% decrease and 0.0881% increase in CEI for provinces with low and high levels of technological innovation, respectively. Therefore, the threshold effect of tax competition on CEI is validated.

5.3 Results of the capital mechanism analysis

To validate the capital mechanism through which tax competition affects CEI, Equation (A12) in Appendix 5 without (Model 1) and with (Model 2) control variables is presented in Table 5, while Equation (A13) using the binary contiguity weights (Model 1), 700km-distance weights (Model 2), and 800km-distance weights (Model 3) is presented in Table 6. As indicated by significant $\ln TAXE$ in Table 5 and $\ln CAP$, $\ln TAXE(0)$, and $\ln TAXE(1)$ in Table 6, the mediating role of capital mobility is confirmed across different spatial weight matrices, which is further measured and reported in Table 7. The mediating effect of capital mobility primarily depends on firms' technology demands. Although provinces with high levels of technological innovation face higher R&D expenditure and stricter tax collection and management systems, they usually provide higher managerial efficiency, diverse talent projects, and higher accessibility and connectivity. This improves provinces' fiscal abilities and provision of public goods, attracting more firms with a high demand for technology. In contrast, firms with low technology demands are more likely to move to provinces with low levels of technological innovation due to the tax incentives provided.

Table 5 Estimation results of mediation analysis-Capital mobility

Variable	$\ln CAP$ (Model 1)	$\ln CAP$ (Model 2)	$SEClabor$ (Model 3)	$TERlabor$ (Model 4)
Constant	10.17***	0.666	-0.266	1.867***
	(0.324)	(1.092)	(1.319)	(0.576)
$\ln TAXE$	-0.922***	-0.289***		
	(0.173)	(0.0842)		
$\ln PGDP$		0.852***	0.111	0.000334
		(0.101)	(0.132)	(0.0282)
$\ln TEC$		0.352***	-0.0569*	0.0188*
		(0.0269)	(0.0299)	(0.0108)
$\ln URB$		-1.446***	-0.389	-0.132
		(0.256)	(0.307)	(0.0910)
$\ln EDU$		0.508***	0.164	0.0187
		(0.123)	(0.151)	(0.0369)
$\ln INS$		0.866***	-0.0657	0.0798**
		(0.128)	(0.135)	(0.0371)
$\ln RFDI$		-0.218***	0.111**	-0.0239**
		(0.0423)	(0.0494)	(0.00977)
$\ln TCG$		-0.163***	0.000216	-0.00367
		(0.0204)	(0.0228)	(0.00264)
$\ln FOREST$		0.282***	0.0254	-0.200***
		(0.0360)	(0.0402)	(0.0590)
N	30	30	30	30
T	14	14	14	14
Individual effect	Controlled	Controlled	Controlled	Controlled
R^2	0.0683	0.8554	0.5962	0.3013

Notes: Standard errors are included in parentheses. Model 1 excludes control variables and Model 2 includes all control variables. Model 3 is estimated for the secondary industry, while Model 4 is for the tertiary industry. ***, ** and * indicate statistical significance at 1%, 5% and 10% level, respectively.

Table 6 Estimation results of mediation analysis-CEI

Variable	$\ln CEI$ (Model 1)	$\ln CEI$ (Model 2)	$\ln CEI$ (Model 3)
ρ	0.0648***	0.0652***	0.0607***
	(0.0266)	(0.0222)	(0.0242)
$\ln CAP$	0.06**	0.0714***	0.06***
	(0.0273)	(0.0266)	(0.027)
$\ln TAXE$ (0)	-0.0515**	-0.0534**	-0.0514**
	(0.0309)	(0.0322)	(0.0295)
$\ln TAXE$ (1)	0.056***	0.0499**	0.0546***
	(0.0214)	(0.0222)	(0.0208)
Threshold value	6.42***	6.74**	6.42**
$\ln TEC$	(2.75)	(2.92)	(2.79)
$\ln POP$	0.051	0.0489	0.0588
	(0.166)	(0.156)	(0.173)
$\ln PGDP$	-0.7010***	-0.7000***	-0.6980***
	(0.0502)	(0.0548)	(0.0547)
$\ln TEC$	0.0569***	0.0597***	0.0576***
	(0.0204)	(0.0228)	(0.0212)
$\ln URB$	-0.304**	-0.394***	-0.328**
	(0.157)	(0.163)	(0.162)
$\ln EDU$	0.0417	0.0577	0.0411
	(0.0448)	(0.0506)	(0.0566)
$\ln INS$	0.2140***	0.2060***	0.2200***
	(0.0663)	(0.0666)	(0.0630)
$\ln RFDI$	-0.0481***	-0.0378**	-0.0440***
	(0.0189)	(0.0188)	(0.0182)
$\ln TCG$	-0.00936*	-0.00792**	-0.0089**
	(0.00589)	(0.00475)	(0.0052)
$\ln FOREST$	0.0515	0.0295	0.0434
	(0.0904)	(0.0875)	(0.0892)
N	30	30	30
T	14	14	14
Individual effect	Controlled	Controlled	Controlled
R^2	0.9831	0.9689	0.9798

Notes: Standard errors are included in parentheses. Models 1, 2 and 3 use the binary contiguity weights, 700km-distance weights, and 800km-distance weights, respectively. ***, ** and * indicate statistical significance at 1%, 5% and 10% level, respectively.

Table 7 Measure of mediation analysis

	Mediation (%)	
	(0)	(1)
W_1	72.22	62.79
W_2	173.69	90.18
W_3	137.27	76.94

Notes: W_1, W_2 and W_3 represent the binary contiguity weights, 700km-distance weights, and 800km-distance weights, respectively. (0) indicates the regime below the threshold value and (1) indicates the regime above the threshold value.

Now, the next issue is to examine whether higher technological innovation attracts firms with low emissions (e.g., knowledge- and technology-intensive service firms) and crowds out firms with high emissions (e.g., energy- and labor-intensive industrial firms). To do so, labor mobility is used as a proxy for firms' capital type to determine underlying interactions with technological innovation. The primary rationale for using labor mobility is that capital usually flows with massive labor migration to achieve higher capital returns and the loss of labor would further restrain capital investment (Rappaport, 2005). According to Yang (2019), the growth rate of labor ($labor = \frac{labor_t - labor_{t-1}}{labor_{t-1}}$) can be calculated to represent labor mobility in a province's secondary ($SEClabor$) and tertiary industries[3] ($TERlabor$), and the impact of technological innovation on labor mobility can be captured by the following fixed-effect panel regression model with estimation results in Table 5.

$$labor_{it} = \ln TEC_{it} \cdot \beta + \mathbf{control_{it}} \cdot \boldsymbol{\gamma}' + \alpha_i + \varepsilon \tag{16}$$

where $labor_{it}$ represents labor mobility in province i in year t, α_i is the fixed effect, and ε is the corresponding error term.

As shown in Table 5, $\ln TEC$ has a significantly negative (−0.0569) impact on $SEClabor$ and a significantly positive (0.0188) impact on $TERlabor$, indicating that a 1% increase in a province's technological innovation will generate a 0.0569% decrease in labor mobility in its secondary industry, and a 0.0188% increase in its tertiary industry. Therefore, it can be argued that provinces with high levels of technological innovation are more likely to attract firms with high technology demands because they provide a better environment for firms to

[3] *Primary industry* refers to agriculture, forestry, animal husbandry, and fishery industries (not including services in support of agriculture, forestry, animal husbandry, and fishery industries). *Secondary industry* refers to mining and quarrying (not including support activities for mining), manufacturing (not including repair service of metal products, machinery and equipment), production and supply of electricity, heat, gas and water, and construction. *Tertiary industry* refers to all other economic activities not included in the primary or secondary industries (http://www.stats.gov.cn/tjsj/ndsj/2020/indexeh.htm).

acquire, learn, and develop new technologies. However, higher costs of technological innovation in these provinces crowd out firms with low technology demands, which is further promoted by tax incentives offered by provinces with low levels of technological innovation.

In addition, results in Appendix 6 indicate three main findings. First, clear spatial heterogeneity of the impact of tax competition on CEI is supported by $\ln TAXE$ (0), implying that if $\ln TEC$ is below the threshold value, higher tax collection and management efficiency (lower tax competition) can significantly decrease CEI in the eastern and central regions but significantly increase CEI in the western region. Second, using a two-period lagged tax competition variable ($lag2\_\ln TAXE$) as the IV and a two-stage least-squares (2SLS-IV) regression model, we find that the variables' potential endogeneity can be avoided, indicating that the findings of this study are reliable and robust. Third, using science and technology expenditure[4] as an alternative indicator of technological innovation for a robustness check, we find that the impacts of lower tax competition on CEI are consistently negative across models if technological innovation is below the threshold value and become positive if technological innovation is above the threshold value, confirming that the main findings of this study are robust.

6. Conclusions

China is undertaking tremendous efforts to transition from coal and petroleum to cleaner energy sources to achieve its ambitious goals of carbon peak, carbon neutrality, and stable economic growth. Using a balanced provincial panel dataset in China over the period 2005–2018, we show that the incorporation of positive spatial dependence of CEI into a panel threshold regression model with fixed effects can significantly increase its goodness-of-fit and achieve a higher coefficient of determination. Thus, this spatially explicit approach improves the policy relevance of such analysis.

The main policy relevant findings are threefold. First, the impact of tax competition on CEI depends on technological innovation. If technological innovation is relatively low, (i.e., below a certain threshold value), higher tax collection and management efficiency (lower tax competition) tends to decrease CEI; otherwise, lower tax competition will usually increase CEI. Second, the role of capital mobility in mediating the impact of tax competition on CEI is confirmed, indicating that more firms with high technology demands will potentially move into provinces with high levels of technological innovation and crowd out firms with low technology demands. Further, the results of spatial heterogeneity analysis, and the endogeneity test and robustness check, indicate that findings of this study are reliable and robust. Third, the roles of central and local governments in designing tax competition policies for achieving the dual goals of carbon emissions reduction and stable economic growth are highlighted. More specifically, diffusion and transport effect of

[4] Data on expenditure for science and technology were collected from Finance Yearbook of China (Long et al., 2016).

carbon emissions requires the central government to coordinate carbon emission reduction goals among provinces and to develop cross-provincial collaboration on taxation policies to advance the transition to a low-carbon economy. Meanwhile, local governments in provinces with high levels of technological innovation can use tax competition to attract more knowledge- and technology-intensive firms, and to promote technological innovation; they can also use it to help build advanced industrial chains, all of which helps reduce CEI. For high-carbon emission projects proposed in provinces with low levels of technological innovation, the central government can raise capital entry barriers and guide local governments to attract more projects with high returns and low carbon emissions, which will stop or slow the race to the bottom. For example, the central government can require firms to implement green projects and establish a reward and punishment mechanism for their carbon emissions.

Despite the robustness of our results, the research from this study can still be extended in a few different ways. A natural extension would be to explore in more depth the balance between tax competition and technological innovation that leads to a low-carbon economy. The second extension would be to compare the emissions reduction performance of different forms of tax competition. Third, the proposed spatial panel threshold model could be extended to address spatial dependence among the identified determinants of carbon emissions. In addition, future research could focus on assessing the economic, environmental, health, and employment impacts of carbon emissions mitigation using different econometric models.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

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Appendix 1

The social planner aims to maximize the whole society's welfare, which can be formulated as the following problem:

$$\max \quad \int_0^{\infty} \left(\ln C - \beta \ln P\right) e^{-\rho t} dt$$

$$s.t. \begin{cases} \dot{P} = \Omega \Upsilon^{\omega} \Lambda^{-\varphi} = \Omega \Lambda L_Y^{\alpha\omega} K^{(1-\alpha)\omega} \\ \dot{K} = Y - C = \Lambda L_Y^{\alpha} K^{1-\alpha} - C \end{cases} \tag{A1}$$

where Λ and C are control variables, while P and K are state variables. Notably, to focus on investigating how the impact of tax competition on carbon emissions depends on technological innovation and transmits through capital mechanism, the constructed endogenous growth model does not consider factors such as real business cycle, price rigidity, inflation, and monetary growth. Hence, the Hamiltonian function of the above social optimization problem can be written as follows:

$$J = \ln C - \beta \ln P + \lambda_1 \Omega \Lambda L_Y^{\alpha\omega} K^{(1-\alpha)\omega} + \lambda_2 (\Lambda L_Y^{\alpha} K^{1-\alpha} - C) \tag{A2}$$

The first-order conditions for maximizing J with respect to Λ and C are as follows:

$$\frac{\partial J}{\partial \Lambda} = \lambda_1 \Omega L_Y^{\alpha\omega} K^{(1-\alpha)\omega} + \lambda_2 L_Y^{\alpha} K^{1-\alpha} = 0 \tag{A3}$$

$$\frac{\partial J}{\partial C} = \frac{1}{C} - \lambda_2 = 0 \tag{A4}$$

Then, the Euler equations are given as follows:

$$\dot{\lambda}_1 = \rho \lambda_1 - \frac{\partial J}{\partial P} = \rho \lambda_1 + \beta \frac{1}{P} \tag{A5}$$

$$\dot{\lambda}_2 = \rho \lambda_2 - \frac{\partial J}{\partial K} = \rho \lambda_2 - \lambda_1 \left(1-\alpha\right) \omega \Lambda L_Y^{\alpha\omega} K^{(1-\alpha)\omega - 1} - \lambda_2 \left(1-\alpha\right) \Lambda L_Y^{\alpha} K^{-\alpha} \tag{A6}$$

together with the transversality conditions: $\lim_{t\to\infty} \lambda_1 P e^{-\rho t} = 0$ and $\lim_{t\to\infty} \lambda_2 K e^{-\rho t} = 0$. Solving the dynamic system, the optimal path of C can be written as follows:

$$\frac{\dot{C}}{C} = -\frac{\dot{\lambda}_2}{\dot{\lambda}} = \left(1-\alpha\right)\left(1 - \frac{\omega\Lambda}{\Omega}\right)\frac{Y}{\Lambda K} - \rho \tag{A7}$$

Using the evolution equation for C and the Euler equation, P can be expressed as follows:

$$P = \frac{\beta C \Omega L_Y^{\alpha\varphi} K^{\omega - \alpha\omega + \alpha}}{\left(1-\alpha\right)\left(\frac{Y}{\Lambda} - \frac{\omega Y}{\Omega} + \varphi\right)} \tag{A8}$$

Appendix 2

Table A1 Summary of data measurement and references

	Variable	Measurement (unit)	References
Dependent variable	Carbon emission intensity ($\ln CEI$)	Ratio of CO_2 emissions from energy consumption to GDP (kg/10^9 Yuan)	Ang and Su (2016)
Factor of interest	Tax competition ($\ln TAXE$)	Ratio of the actual tax revenues to tax capacities (%)	Mkandawire (2010)
Threshold variable	Technology ($\ln TEC$)	Patent counts granted (piece)	Zhang et al. (2020a)
Mediator variable	Capital mobility ($\ln CAP$)	Self-raised funds in fixed assets of (100 million Yuan)	Fu and Geng (2011)
Control variables	Population ($\ln POP$)	Permanent residents at the end of each year (10^4 persons)	Chen and Lei (2018)
	Economic development ($\ln PGDP$)	Per capita GDP (Yuan)	Chen and Lei (2018)
	Technology ($\ln TEC$)	Patent counts granted (piece)	Zhang et al. (2020a)
	Urbanization ($\ln URB$)	Ratio of urban population (%)	Li et al. (2018)
	Education ($\ln EDU$)	Weighted average of the total years of education (Years)	Leng and Du (2016)
	Industrial structure ($\ln INS$)	Ratio of the added value of the secondary industry to GDP (%)	Li et al. (2018)
	Foreign direct investment ($\ln RFDI$)	Ratio of foreign direct investment to GDP (%)	Zhou et al. (2018)
	Energy consumption ($\ln TCG$)	Ratio of the total energy consumption measured in standard coal equivalent to GDP (kgce)	Chen and Lei (2018)
	Forest coverage ($\ln FOREST$)	Ratio of the forest area to total regional land area (%)	Waheed et al. (2018)

Appendix 3

Tax competition is represented by ($\ln TAXE$) and measured by the ratio of the actual tax revenue ($taxg$) to tax capacity. $Taxg$ is unobservable but can be indirectly measured by the regression in Equation (A9) as the fitted tax revenue, using $taxg$ as the dependent variable and different types of tax bases as independent variables, can appropriately reflect a region's tax capacity. Notably, for China, Li and Lei (2021) identified five main indicators of local tax bases, including the ratio of export and import to GDP ($trag$), the ratio of secondary industry added value to GDP ($secg$), the ratio of tertiary industry added value to GDP (thg), population ($\ln pop$), and per capita GDP ($\ln pgdp$). The regression model can be specified as:

$$taxg_{it} = \alpha + \alpha_1 trag_{it} + \alpha_2 secg_{it} + \alpha_3 thg_{it} + \alpha_4 \ln pop_{it} + \alpha_5 \ln pgdp_{it} + \mu_{it} \tag{A9}$$

where $taxg_{it}$ represents province i's share of tax revenue to GDP in year t, α is the intercept, and μ is the error term.

Appendix 4

As widely observed, air pollutant emissions (CO_2, SO_2, NO_x, $PM_{2.5}$) are usually spatially dependent due to diffusion and transport effects and ever-increasing economic interactions among different provinces (Zhang et al., 2020b; Ren and Matsumoto, 2020). This spatial observation can be further confirmed using the global and local Moran's *I*s in Equations (A10) and (A11) (Moran, 1950).

$$\mathrm{I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(y_i - \bar{y}\right)\left(y_j - \bar{y}\right)}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \tag{A10}$$

$$\mathrm{I}_i = \frac{n\left(y_i - \bar{y}\right)\sum_{j=1}^{n} W_{ij}\left(y_j - \bar{y}\right)}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \tag{A11}$$

where n is the number of provinces, y_i and y_j are the CEI in provinces i and j, respectively, $\bar{y}$ is the mean of CEI, and W_{ij} is the element of the spatial weight matrix W with $\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij} = n$. As found in Equations (A10) and (A11), Moran's *I* lies between −1 and 1. A positive Moran's *I* implies positive spatial dependence, indicating that provinces with high or low CEI tend to spatially cluster, whereas a negative Moran's *I* indicates that provinces with high and low CEI tend to spatially disperse.

Appendix 5

We employ the following mediator model to validate the capital mechanism through which tax competition influences CEI (Acemoglu, 2003; Wen and Ye, 2014).

$$\ln CAP_{it} = \ln TAXE_{it} \cdot \beta + u_i + \varepsilon_{it} \tag{A12}$$

$$\begin{aligned} \ln CEI_{it} = {} & \rho \cdot W \cdot \ln CEI_{it} + \ln TAXE_{it} \cdot \mathrm{I}\left(\ln TEC_{it} \le \gamma\right) \cdot \beta_1 + \ln TAXE_{it} \cdot \mathrm{I}\left(\ln TEC_{it} > \gamma\right) \cdot \beta_2 \\ & + \mathbf{control}' \cdot \Theta + \beta_3 \cdot \ln CAP_{it} + u_i + \varepsilon_{it} \end{aligned} \tag{A13}$$

where $\ln CAP$ represents the mediating variable, $\beta_i (i = 1,2,3)$ are parameters to be estimated, and other variables are defined as above. Accordingly, the mediating effect of $\ln CAP$ can be validated by testing the significance of β in Equation (A12) and $\beta_i (i = 1,2,3)$ in Equation (A13), indicating that the mediating effect exists if there are significant β, declining or insignificant $\beta_i (i = 1,2)$, and significant β_3, but there is no mediating effect if there are significant β, significant $\beta_i (i = 1,2)$, and insignificant β_3. A partial mediating effect can be detected if there are significant β, β_3, and insignificant changes in $\beta_i (i = 1,2)$, which is measured by $mediation(0) = \beta_3 \beta / \beta_{11}$ and $mediation(1) = \beta_3 \beta / \beta_{12}$, respectively.

Another important construct for the spatial panel threshold model with fixed effects is W, which can be based on boundaries or distances (Kelejian and Robinson, 1995). A simple case of the boundary-based W uses the binary contiguity weights and assumes that only contiguous provinces influence one another. As a result, the element W_{ij} is equal to 1 if two provinces share boundaries, and 0 otherwise. In practice, W is usually row normalized with the condition of $\sum_{j=1}^{n} W_{ij} = 1, i = 1, \cdots, n$. Alternatively, we define a radial distance-based W as $W_{ij} = \begin{cases} 1, & d_{ij} < d' \\ 0, & d_{ij} \ge d' \end{cases}$, where d_{ij} denotes the geographical distance between provinces i and j, and d' denotes the threshold distance. To obtain W, d_{ij} is calculated by using provincial capital cities' coordinates to represent the center of the province, while d' is 700 and 800 km in this paper. In so doing, we ensure that all provinces except Xinjiang[5] have at least one neighbor and ensure the reliability and robustness of the spatial analysis.

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[5] Due to Xinjiang's vast territory, its capital is far from any other provincial capital city.

Appendix 6

Spatial heterogeneity analysis

Referencing the classification standard published by the National Bureau of Statistics[6], we classify the sample into the eastern, central, and western region subsamples, re-estimate the spatial panel threshold effect model with fixed effects, and present the estimation results in Table A2 to further examine the spatial heterogeneity of the impact of tax competition on CEI. Compared with the estimation of national results in Table 4, significant positive spatial dependence is confirmed in the central (0.0640) and western (0.0481) regions but not in the eastern region, based on its insignificant spatial correlation coefficient. Significant threshold values of $\ln TEC$ are 8.7608 for the eastern region, 7.2828 for the central region, and 10.7884 for the western region. Significant and positive $\ln TAXE$ (1) in all regions indicate that higher tax collection and management efficiency (lower tax competition) can increase local CEI if $\ln TEC$ is above the threshold value; however, clear spatial heterogeneity is suggested by $\ln TAXE$ (0), implying that if $\ln TEC$ is below the threshold value, higher tax collection and management efficiency (lower tax competition) can significantly decrease CEI in the eastern and central regions but significantly increase CEI in the western region. A possible reason is that different regions have different industrial structures, forest endowments, and stages of economic development. On average, the eastern region is more developed with a higher concentration of knowledge- and technology-intensive industries, making it more likely to attract firms that consume fewer fossil fuels and have higher emissions reduction capacities. Considering the diffusion and transport effects, rich forest endowment in the eastern region absorbs carbon emissions, contributing to decreased CEI. As expected, the central region and the nation overall exhibit similar impacts of tax competition on CEI due to comparable levels of economic development, technological innovation, and forest coverage. As a less developed region, higher tax competition (lower tax collection and management efficiency) in the western region promotes economic development faster than carbon emissions, leading to a lower CEI.

Table A2 Results of spatial heterogeneity analysis

Variable	$\ln CEI$ (Eastern region)	$\ln CEI$ (Central region)	$\ln CEI$ (Western region)
ρ	0	0.0640***	0.0481*
	(0.0086)	(0.0238)	(0.0281)
$\ln TAXE$ (0)	-0.0396***	-0.1995***	0.1088***
	(0.0036)	(0.0096)	(0.0048)
$\ln TAXE$ (1)	0.0284***	0.0483***	0.0128***
	(0.0041)	(0.0038)	(0.0055)
Threshold value			
$\ln TEC$	8.7608***	7.2828***	10.7884***
	(2.2942)	(1.8026)	(2.4256)

[6] Eastern region includes Beijing, Tianjing, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan; Central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan; Western region includes Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangzhou, Inner Mongolia Autonomous Region.

$\ln POP$	0.1235***	1.0212***	0.1113*
	(0.0211)	(0.0819)	(0.0582)
$\ln PGDP$	-0.4613***	-0.9178***	0.1268***
	(0.0078)	(0.0098)	(0.0164)
$\ln TEC$	-0.0418***	0.0968***	0.0630***
	(0.0040)	(0.0037)	(0.0048)
$\ln URB$	0.3609***	0.0813**	-1.9270***
	(0.0248)	(0.0319)	(0.0561)
$\ln EDU$	0.1013***	0.2571***	-0.8438***
	(0.0077)	(0.0135)	(0.0150)
$\ln INS$	0.3937***	0.0826***	0.2828***
	(0.0147)	(0.0107)	(0.0260)
$\ln RFDI$	0.0196***	-0.1382***	0.0382***
	(0.0044)	(0.0058)	(0.0039)
$\ln TCG$	-0.0092***	-0.0138***	-0.0011
	(0.0008)	(0.0011)	(0.0011)
$\ln FOREST$	0.0655***	0.0459*	0.4280***
	(0.0106)	(0.0230)	(0.0260)
N	12	9	9
T	14	14	14
Individual effect	Controlled	Controlled	Controlled
R^2	0.1701	0.9869	0.9783

Notes: Standard errors are included in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% level, respectively.

Endogeneity check

We next check the variables' potential endogeneity as related to omitted variables, measurement errors, and simultaneity, possibly leading to low efficient and biased estimators (Wooldridge, 2015). Although, to a certain extent, the proposed spatial panel threshold model with fixed effects can eliminate endogeneity, this paper employs the instrumental variable (IV) method to further address endogeneity. To achieve this, we apply a two-period lagged tax competition variable ($lag2\_\ln TAXE$) as the IV and estimate the two-stage least-squares (2SLS-IV) regression model. Technically speaking, the IV should be uncorrelated with error terms (the first stage) but strongly correlated with the dependent variable (the second stage) when other independent variables are controlled for (Stocl and Watson, 2003). The estimation results for the first and second stage regression models are presented in Columns 2 and 3 in Table A3, respectively, revealing that the significant $lag2\_\ln TAXE$ for the first stage and the significant $\ln TAXE$ (0), $\ln TAXE$ (1), and $\ln TEC$ for the second stage satisfy that the above IV requirement and the findings of this paper are reliable and robust.

Table A3 Results of 2SLS-IV estimation and robustness test

Variable	$\ln TAXE$ (1st-stage)	$\ln CEI$ (2nd-stage)	$\ln CEI$ (Model 1)	$\ln CEI$ (Model 2)	$\ln CEI$ (Model 3)
ρ		0.0851***	0.0719***	0.0796***	0.0805***
		(0.0275)	(0.0257)	(0.0238)	(0.0245)
$\ln TAXE$ (0)		-0.0256**	-0.0559**	-0.0624**	-0.0358*
		(0.0102)	(0.0332)	(0.0288)	(0.0257)
$\ln TAXE$ (1)		0.0253**	0.0337*	0.0316*	0.0392**
		(0.0103)	(0.0212)	(0.0212)	(0.0216)
Threshold value					
$\ln TEC$		10.9800***	6.5527**	6.5913**	6.5800***
		(2.6685)	(2.8740)	(2.8418)	(2.8104)
$lag2\_\ln TAXE$	0.288***				
	(0.0309)				
$\ln POP$	-0.167***	0.4027***	0.1358	0.35675**	-0.0595
	(0.0326)	(0.0314)	(0.1780)	(0.1755)	(0.1653)
$\ln PGDP$	0.00678	-0.06125***	-0.6435***	-0.5759***	-0.6088***
	(0.0464)	(0.0245)	0.0490	(0.0490)	(0.0453)
$\ln TEC$	0.0314*	-0.15195***	0.0602***	0.020873	0.0379**
	(0.0187)	(0.0100)	(0.0198)	(0.0209)	(0.0211)
$\ln URB$	0.260**	-0.6532**	-0.0936	-0.085749	-0.1446
	(0.106)	(0.0078)	(0.1517)	(0.1633)	(0.1682)
$\ln EDU$	-0.256***	0.15855***	-0.0085	-0.050105	-0.0187
	(0.0514)	(0.0103)	0.0508	(0.0513)	(0.0515)
$\ln INS$	-0.126***	-0.05465***	0.1217*	0.1104*	0.0808
	(0.0480)	(0.0027)	(0.0753)	(0.0673)	(0.0661)
$\ln RFDI$	-0.00587	-0.00745***	-0.0605***	-0.0385**	-0.0842***
	(0.0160)	(0.0009)	(0.0184)	(0.0166)	(0.0173)
$\ln TCG$	-0.0313***	0.07955***	-0.0043	-0.0187***	-0.0095**
	(0.00859)	(0.0135)	(0.0051)	(0.0054)	(0.0054)
$\ln FOREST$	0.0122	0.06955***	-0.0037	0.033408	0.1885**
	(0.0145)	(0.0035)	(0.0909)	(0.0855)	(0.0994)
N	30	30	30	30	30
T	12	12	13	13	13
Individual effect	Controlled	Controlled	Controlled	Controlled	Controlled
R^2	0.6670	0.9893	0.9808	0.9849	0.9902
First-stage *F*-statistic	69.93***				

Notes: Standard errors are included in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% level, respectively.

Robustness check

We next examine science and technology expenditure[7] as an alternative indicator of technological innovation and re-estimate the model. As suggested by Long et al. (2016), the ratio of local expenditure for science and technology to general public budget expenditure can also reflect local awareness and capacities of technological innovation. Equation (15) is re-estimated and reported in Table A3. A comparison between the results of Tables 4 and A3 reflects that the incorporation of spatial effect significantly improves model performance by achieving a higher R^2. Spatial correlation coefficients are found to be 0.0719 for Model 1 using binary contiguity weights, 0.0796 for Model 2 using 700km-distance weights, and 0.0805 for Model 3 using 800km-distance weights, indicating the spatial dependence of CEI in China over the sample period. Significant $\ln TEC$, $\ln TAXE$ (0), and $\ln TAXE$ (1) across models confirm a threshold effect of tax competition on CEI. Specifically, the impacts of tax collection and management efficiency (lower tax competition) on CEI are consistently negative across models if technological innovation is below the threshold value and become positive if technological innovation is above the threshold value, confirming that the main findings of this study are robust.

[7] Data on expenditure for science and technology were collected from Finance Yearbook of China (Long et al., 2016).