Local and spatial spillover effects of corporate financing costs on regional carbon emissions: evidence from Chinese listed firms

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Abstract
The signing of the Paris Agreement has raised concerns about global carbon emissions, which have detrimental consequences in terms of climate change. At the same time, the financing process for listed companies has begun to incorporate investigations into these firms’ carbon emissions. But the current impact of financing costs on firms’ carbon emissions has not been accurately assessed. There are large differences in endowments in different regions of China, and factors flow frequently among regions. To date, no empirical evidence has emerged to show the spatial effects of financing costs on carbon emissions. This study uses the STIRPAT model and a panel lag regression model for empirical testing. The results show that increasing financing costs will increase the burden imposed by carbon reduction efforts in various regions. Although this trend has obvious spillovers to surrounding areas, the location of the enterprise bears a more negative burden of externalities. Further analysis shows that reducing the financing costs of enterprises in economically developed regions can reduce both their carbon emissions and the damage to economic growth. These research conclusions can help policymakers shape carbon reduction activities through reducing corporate financing costs on the basis of regional development differences.

Keywords Local effect · Spatial effect · Financing costs · Carbon emissions

Introduction
Climate change is one of the major challenges facing the world today. Approximately, 51 billion tons of greenhouse gases is emitted into the atmosphere globally each year. As part of the effort to mitigate the damage caused by greenhouse gases such as carbon dioxide, the Paris Agreement, which was completed in December 2015, determined emission reduction plans and goals for all of its signatory states. In turn, countries around the world are now implementing large-scale cooperative actions to achieve carbon neutrality goals. The issue of carbon emissions is of great significance to the sustainable development of the world’s resources and environment. According to research carried out by the International Energy Agency (IEA), the total carbon dioxide emissions of China—the world’s second largest economy—account for one-fourth of the world’s total, so China plays an important role in addressing global carbon emissions and climate change. At the 75th United Nations General Assembly, China formally proposed a “dual carbon” goal, striving to reach its peak of carbon dioxide emissions by 2030 and to achieve a balance between “carbon emissions” and “carbon absorption” by 2060.

The development of the financial industry plays an important role in reducing carbon emissions. On the one hand, it provides a financing platform for enterprises; on the other hand, it provides a convenient channel for investment behavior. Through this mechanism, enterprises benefit from the pressure exerted by the financial industry to reduce R&D costs, promote green economic growth, and improve environmental quality. Traditional financial services do not consider the negative externalities brought about by corporate environmental behavior, but only focus on ways to maximize profits from the perspective of economic feasibility and financial returns. In the context of low-carbon goals,
However, financial services take negative externalities into account in the process of measuring allocation efficiency, and they regulate the behavior of individuals and enterprises by adjusting the flow of funds.

In the Sustainable Development Goals report authored by Garroway and Carpenter, it is proposed that the key to helping countries achieve such goals is to improve deficiencies in financing (Sinha et al. 2021). The United Nations Global Compact has also pointed out that to accelerate countries’ efforts to address climate change and achieve sustainable development, the most important consideration is to reposition the global capital market—a process that requires adjustment of corporate financing mechanisms. As part of this pursuit, stakeholders have begun to pay extensive attention to corporate carbon emissions, investment trends have shifted to favor green and low-carbon investments, and new financial instruments such as green bonds and ESG (environmental, social, and governance) funds have emerged one after another, further narrowing the financing channels open to the high-carbon energy industry and forcing enterprises to consider limiting their carbon emissions (Sinha et al. 2021).

In the study of carbon emissions, reducing the total amount of carbon emissions has been widely recognized as a desirable international goal, but there is controversy over the impacts of the financial industry on carbon emissions. Tamazian et al. (2009) asserted that the development of the financial industry can reduce corporate financing costs, enrich corporate financing channels, promote energy-saving production, and reduce carbon emissions by encouraging companies to innovate in regard to their production technologies. However, Işık et al. (2017) found that the development of the financial industry increased carbon dioxide emissions when studying the Greek problem. Sadorsky (2010) suggested that the development of financing avenues, especially the improvement of corporate financing capabilities, will motivate companies to seek out more investment projects, further expand the scale of their production and operations, and lead to increased energy consumption. In addition, Dogan and Turkekul (2016) found that financial development does promote economic development in the short term, but does not have a significant impact on environmental pollution. Thus, the evidence on how corporate financing affects carbon emissions remains contradictory. In addition, the conclusions reached vary according to the specific research context and may not relate to the decarbonization scenario posited in the current research.

In China, there are obvious differences in the level of economic development and resource endowments in various regions, and enterprises frequently conduct cross-regional flow of factors, leading to significant spatial effects on carbon emissions. Thus, if a unified national carbon reduction program is implemented, the rights and responsibilities associated with carbon emissions in various regions will not be equal—which may not only fail to curb carbon reduction, but also hinder the economic development of some regions. To account for this perspective, this study is based on the data of listed companies in China, combined with the data on the development of various regions in China; it also reflects the financing situations of enterprises with financing costs and discusses the previously mentioned spatial effects of carbon reduction in China.

Our research makes important contributions from three perspectives. First, most of the literature has ignored the externalities of financial services in the context of low-carbon target development, and few studies have addressed the impact of financing costs on carbon emissions. Our study refines the research perspective to the micro-enterprise level, focusing on the impact of corporate financing costs on regional carbon emissions. Second, our study breaks new ground by incorporating the spatial effects into the framework used for analyzing the impact of financing cost on regional carbon emissions. The STIRPAT model and a spatial lag regression model are used to study local effects and peripheral spillover effects. Finally, our research focuses on carbon emissions while simultaneously taking regional economic development into account and introduces a “regional decoupling index,” which measures the process of breaking the link between economic activity and the environment, as a means to achieve a win–win situation for both carbon reduction and economic growth.

Literature review and hypothesis development

Effect of financing costs on carbon emissions

In prior research on carbon emissions, many scholars have focused on the famous environmental Kuznets curve (EKC) hypothesis, and some studies have considered the form of EKC exhibited by the manufacturing industry (Işık et al. 2019; İşik et al. 2019; İsik et al. 2021; Ongan et al. 2021) to study the relationship between carbon dioxide and other greenhouse gas or environmental pollutant emissions and economic growth and energy consumption. Noting the different performances of agriculture, forestry, and animal husbandry in the EKC hypothesis, one study concluded that considering the different impacts of the three was important to comprehensively implement measures to reduce carbon emissions (Rehman et al. 2021). Some scholars proposed to incorporate production and consumption into the analytical framework to use the ecological footprint to measure the degree of environmental degradation (İşik et al. 2021; Khan et al. 2021; Sharif et al. 2019). In addition to studying traditional industries, Ahmad et al. (2021) creatively proposed the heterogeneous effects of inward foreign direct investment.
Financial development is closely related to carbon emissions. As an allocation mechanism, finance not only promotes economic expansion and technological progress, but also plays a role in the choice of production factors, guiding capital and other production factors to stay away from industries with high energy consumption, high carbon emissions, and high pollution. The carbon emission rights and the carbon tax formed under the Coase property rights theory and the Pigou tax theory have resulted in the internalization of firm costs associated with such factors (Wei and Yang 2022). To help firms cope with the increasing carbon reduction costs they must bear, financial institutions need to support the firms by developing financial design systems that are compatible with the structure of the environment (Lin et al. 2021).

With the development of supportive financial factors, especially improvement in firms’ ability to obtain credit, the firms will be able to seek out more investment projects and further expand the scale of their production and operations, which will in turn lead to an increase in their energy consumption (Sadorsky 2010). From consumers’ perspectives, booming financial markets tend to stimulate domestic consumption, and this increase in demand for various household items then leads to greater energy consumption and environmental pollution through increased production (Zhang 2011). Xiong and Qi (2016), taking China as their research object, used the generalized method of moments (GMM) regression estimation method to draw the conclusion that the deterioration of air quality is closely related to the level of financial development—a revelation that prompted emission reduction policymakers in various regions began to pay more attention to the development of the financial field.

According to Porter’s theory, firm financing is a key financial activity that can stimulate more investment in R&D by firms and encourage them to upgrade equipment or invest in new technologies that can reduce their carbon emissions (Petroni et al. 2019). At the same time, the external pressure of financing costs prompts firms to overcome their financing inertia and has a complementary effect with their internal production mechanisms that can further improve the carbon emission problem (Ambec & Barla 2002). In addition, according to information display theory, compared with regulatory policy measures, financing behaviors are mostly carried out in the trading markets, which are prone to information asymmetry and principal–agent problems, thereby affecting firms’ carbon emission decisions. Thus, high financing costs may hinder firms from carrying out carbon reduction activities and reduce their enthusiasm for carbon reduction investments.

This line of theoretical analysis suggests that firm financing behaviors have both positive and negative effects on carbon emissions. To date, however, few studies have directly addressed the impact of financing costs on firm carbon emissions. He et al. (2012) found that when firms pursue financing for technological innovation activities, due to the confidential and proprietary nature of those technologies and the long payback period for investments, the problem of information asymmetry between investment and financing parties often arises, which leads to financing difficulties for firms. As a result, investment of capital in innovative activities such as carbon reduction may not be favored. Ge et al. (2018) showed that firms find it difficult to engage in green technology innovation, and their inability to do so leads to higher carbon emissions. Guariglia and Liu (2014) proposed that investments that aim to reduce carbon emissions are a part of the costs faced by firms, and suggested that firms have insufficient motivation to engage in environmental protection investments when under financing constraints. In addition, Zhang et al. (2019) pointed that managers, as trusted persons in business operations, tend to favor short-term and high-yield projects when under performance pressure, while ignoring long-term investment projects geared toward the goal of carbon reduction. Moreover, as a result of their adoption of low-cost production methods, the carbon emissions of firms have greatly increased.

Based on the preceding arguments, we propose the following hypothesis:

**Hypothesis 1**: financing costs have a significant positive impact on carbon emissions because the positive impact between the two is greater than the negative impact.

**Spatial effects of firm behaviors on carbon emissions**

Most studies on carbon emissions focus on the macrolevel, such as countries and regions, or on the mesolevel, such as industries. Tamazian et al. (2009) used country data to show that the development of the financial industry can reduce financing costs, enrich financing channels, and achieve energy-saving production by promoting innovative production technologies, ultimately reducing carbon emissions. Based on the panel VAR model, Gu and He (2012) found that deepening financial cooperation has, to some extent, reduced carbon emissions by tracking the relationship between availability of financing and carbon emissions in China’s provincial-level regions for 30 years.

Firms are the main entities that shape market behavior as well as the main actors in regard to carbon reduction behavior. Refining the research perspective to the firm level, therefore, can address carbon emissions more specifically. Although microdata for firms are more diverse and less available than data on the level of regions or industries, some scholars have made innovative attempts at firm-level
analysis. Wang and Ni (2016) used a questionnaire survey to collect carbon emission samples from 32 firms in Zhejiang Province, China, and applied the analytic hierarchy process (AHP) model to construct measurement indicators. However, limited by the small sample size, their research conclusions had regional differences. Shen et al. (2017) collected pollutant discharge fee data for 32 companies and carried out a study based on the homology of carbon dioxide and air pollutants. However, missing values and measurement errors have obvious influences on this process. Zhou et al. (2019) were able to expand the sample size by taking S&P 500 companies as the research objects and studied the carbon efficiency of firms by measuring their carbon emissions.

Notably, the preceding studies ignored the spatiality of carbon emissions caused by firm production. With the rise of spatial econometrics, spatial factors have become more widely incorporated into the analysis framework of carbon emissions. When Fisher-Vanden et al. (2004) studied the energy consumption intensity of Chinese industrial firms, they found that carbon dioxide and other gas emissions caused by energy consumption had a significant spatial effect. Khezri et al. (2022) used the spatial Durbin regression model to comprehensively study the possibility of financial development having direct and spillover effects on carbon emissions at the regional level. Their study found that financial development stimulated carbon dioxide emissions, while financial demand in adjacent regions played an important role in a country’s total carbon emission. Using a spatial econometric model, Wang et al. (2021) found that the negative spillover effect of financial development is higher than the positive direct effect. In general, financial development has an adverse impact on carbon dioxide emissions in adjacent areas. Zhao (2003) used adjacency, distance, and gravity matrices to construct a spatial econometric model, finding that fixed asset investment in the financial industry can reduce the local carbon emission level by developing the financial market.

Large differences are evident in the level of economic development and resource endowments in various regions of China. Production factors of firms often flow across regions, such that firms demonstrate spatial dependence and spillover characteristics in the production process. But what are the spatial and temporal characteristics of companies’ impacts on carbon emissions? Zhang and Dou (2016) used a dynamic spatial Durbin model to show that pollution emission intensity has a significant positive spatial correlation and spillover effect. In addition, some studies have found that there is a significant spatial autocorrelation of carbon emissions (Liu and Zhang 2019), and that the regional carbon reduction level is consistent with the development direction of financial efficiency. The key to the positive effect of firm financial development on emissions reduction, it seems, lies in the supervision of funds, not the absolute amount of funds invested (Huang et al. 2014). As yet, however, the literature on carbon emissions under the influence of financing costs remains lacking. To address this gap, our research incorporates the spatial factors into the analysis framework to study the previously mentioned problems.

Based on these arguments, we propose the following hypothesis:

Hypothesis 2: carbon emissions are spatially correlated, and an increase in corporate financing costs will not only increase local carbon emissions but also have spatial spillovers to surrounding areas.

Decoupling analysis of firm-level and regional-level carbon reduction

According to the externality theory, a firm is a rational economic “person” whose purpose is to make a profit. Thus, when determining its goal level of carbon emissions, the firm weighs the carbon reduction cost against the carbon reduction benefit. If a one-sided emphasis on the carbon reduction goals fails to take into account the relevant economic development issues, it will lead to “abandonment of food due to choking.” Promoting the normal operation of the firm under such circumstances will be difficult. At the same time, there are large differences in the level of economic development between regions. When studying carbon emissions, if only the absolute amount of carbon reduction is considered, it is easy to cause the main body of carbon reduction to engage in a carbon-reduction competition, which is inconsistent with each firm’s actual level of development.

As an alternative approach, the Organization for Economic Co-operation and Development (2002) proposed decoupling theory as a vehicle to study the relationship between economic growth and carbon emissions. This theory generally focuses on the process of breaking the link between economic activities and the environment (Enevoldsen et al. 2007). Based on this theory and the preceding arguments, we propose the following hypothesis:

Hypothesis 3: using regions in different “decoupling” states as the classification basis, there are significant differences in the local effects and spatial spillover effects of corporate financing costs on regional carbon emissions.

Using decoupling theory, some earlier studies have explored the dependence between carbon emissions and economic growth. In developing economies, economic development is still the primary focus, so the decoupling trend fluctuates greatly across these countries (Wu et al. 2018). In developed economies, a transition from weak decoupling to strong decoupling appears to be under way, which is gradually resulting in a good separation of economic development and carbon emissions (Wang and Su 2020). When applying decoupling theory, most studies have focused on the national level. In contrast, our research applies decoupling theory to the analysis of regional carbon emissions.
The Tapio decoupling index is used to describe the coupling relationship between regional economic growth and environmental impact (Yasmeen and Tan 2021); it avoids the use of a single absolute or relative measurement and, in turn, minimizes the deviation caused by high sensitivity or extremeness of such an indicator. The Tapio decoupling index is calculated as follows:

$$\text{Topio}_i = \frac{\Delta C_i}{C_i} / \frac{\Delta GDP_i}{GDP_i}$$  \hfill (1)

where $i$ is the region, $C$ is the regional carbon emissions (in units of 10,000 tons), and GDP is the regional gross domestic product (in units of 100 million yuan).

In Eq. (1), $\frac{\Delta C_i}{C_i}$ represents the growth rate of carbon emissions, and $\frac{\Delta GDP_i}{GDP_i}$ represents the economic growth rate. Topio$_i$ represents the decoupling elasticity. The differences in the growth rates of the economy and carbon emissions fall into the categories shown in Table 1.

### Data sources and methodology

#### Data sources

Our sample comprises the annual data of Chinese listed companies from 1998 to 2018, with the data being obtained from the China Stock Market and Accounting Research (CSMAR) database. This database, which was created by China Shenzhen Shishma Data Technology Co., is an authoritative source for the study of China’s economic and financial fields, and is used by many colleges and universities, independent research institutions, and government agencies. The provincial index data come from the China Statistical Yearbook for the years of interest. The carbon emission accounting data come from the China Energy Statistical Yearbook. The carbon emission data are based on the provincial input–output table, and the energy consumption coefficient and the emission coefficient published by the Intergovernmental Panel on Climate Change (IPCC) are used for subsectoral accounting. The accounting content includes 47 sectors and 17 types of energy fossils.

#### Variable selection

**Explained variable**

The carbon emission accounting data are based on the China Emission Accounts and Datasets (CEADs) accounting method. The specific calculation formula is as follows:

$$CE_{ij} = AD_{ij} \times EF_{ij}$$  \hfill (2)

where $AD_{ij}$ represents the consumption of fossil energy $i$ in sector $j$ (in units of 10,000 tons of standard coal), $EF_{ij}$ represents the emission factor, which we obtained by multiplying the combustion value per unit of fossil energy $NVC_i$, the emissions of $CO_2$ per unit of combustion value $CC_i$, and the proportion of oxygen $O_i$. The formula for calculating $EF_{ij}$ is as follows:

$$EF_{ij} = NVC_i \times CC_i \times O_i$$  \hfill (3)

**Explanatory variables and control variables**

The carbon emission accounting results were expressed in InCE. Financing costs (lnPRO) were given in terms of the public company’s share issuance premium (Bolton and Kacperczyk 2021). The age of the company (lnAGE) was calculated as the current year minus the year in which the firm was opened.

### Table 1 Tapio decoupling classification index

| Economic state | Classification index | Tapio index | Decoupling | Implication |
|----------------|----------------------|-------------|------------|-------------|
| Economic growth | $\Delta C > 0$, $\Delta GDP > 0$ | $0 < \text{Tapio} < 0.8$ | Weak decoupling | Carbon emissions are growing slower than economic growth |
| | | $0.8 < \text{Tapio} < 1.2$ | Expansive coupling | Carbon emissions and economic growth are basically synchronized |
| | | $\text{Tapio} > 1.2$ | Expansive negative decoupling | Carbon emissions are outpacing economic growth |
| | $\Delta C < 0$, $\Delta GDP > 0$ | $\text{Tapio} < 0$ | Strong decoupling | Economic growth while reducing carbon emissions |
| Economic recession | $\Delta C < 0$, $\Delta GDP < 0$ | $0 < \text{Tapio} < 0.8$ | Weak negative decoupling | Carbon emissions are falling slower than the economic recession |
| | | $0.8 < \text{Tapio} < 1.2$ | Recessive coupling | Carbon emissions are basically in sync with the economic recession |
| | | $\text{Tapio} > 1.2$ | Recessive decoupling | Carbon emissions are falling faster than the economic recession |
| | $\Delta C > 0$, $\Delta GDP < 0$ | $\text{Tapio} < 0$ | Strong negative decoupling | Economic recession accompanied by carbon emissions |
The logarithm of the firm’s operating income is used to represent firm size (lnSCA). The firm asset structure (lnSTR) was calculated as “(net fixed assets + net inventory)/total assets.” The remaining provincial-level variables were obtained as follows. GDP per capita (lnA) was calculated by dividing the constant-price GDP by the population at the end of the year. Temperature (lnTEM) was represented by the annual mean temperature of the capital city of the province.

The educational level (lnEDU) consisted of the proportion of the population with a high school education or above in the province relative to the population older than age 6. Population density, foreign direct investment, and the proportion of secondary industry were expressed as ln

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respectively. The descriptive statistics for these variables are shown in Table 2.

### Model construction

The STIRPAT model comprehensively considers the main factors affecting regional environmental changes, such as population, economic development level, and technical level; it is widely used in the study of regional behavior and regional environmental changes. Our study draws on the work by Ahmad et al. (2021), which was based on the STIRPAT model (Dietz and Rosa 1997), but extends this model to avoid the randomness of variable selection of carbon emissions influencing factors. Among these factors, the impacts of population, affluence, and energy intensity on carbon emissions have been confirmed in many studies. Our model was calculated as follows:

\[
\ln \text{CE}_i = a + \beta_1 \ln \text{PRO}_i + \beta_2 \ln \text{AGE}_i + \beta_3 \ln \text{SCA}_i + \beta_4 \ln \text{STR}_i + \beta_5 \ln \text{P}_i + \beta_6 \ln \text{FDI}_i + \beta_7 \ln \text{T}_i + \beta_8 \ln \text{EDU}_i + \beta_9 \ln \text{TEM}_i + c_i
\]

where \(a\) is a constant and \(\beta_i - \beta_{10}\) represents the regression coefficient of each variable. Taking the natural logarithm of both sides of Eq. (4) to linearize, it results in the following equation:

\[
\ln \text{CE}_{ct} = \alpha + \beta_1 \ln \text{PRO}_{ct} + \beta_2 \ln \text{AGE}_{ct} + \beta_3 \ln \text{SCA}_{ct} + \beta_4 \ln \text{STR}_{ct} + \beta_5 \ln \text{P}_{ct} + \beta_6 \ln \text{FDI}_{ct} + \beta_7 \ln \text{T}_{ct} + \beta_8 \ln \text{EDU}_{ct} + \beta_9 \ln \text{TEM}_{ct} + \alpha + \mu + \epsilon
\]

where \(c\) is the region, \(i\) is the firm, \(t\) is the year, \(\lambda\) is the time fixed effect, \(\mu\) is the industry fixed effect, and \(\epsilon\) is the random error term. The remaining variables have the same meaning as in Table 2.

Carbon emissions not only depend on the specific region, but also are affected by the interaction of geographically adjacent regions (Zhao and Sun 2022). Taking into account the existence of spatial autocorrelation of carbon emissions, we used the following model used to study regional effects:

\[
\ln \text{CE}_i = \rho W_{P_i} + \phi_1 \ln \text{PRO}_i + \phi_2 \text{firmControls}_{it} + \phi_3 \text{areaControls}_{ct} + \lambda + \mu + \epsilon
\]

where \(\rho\) indicates the direction and extent of the impacts of carbon emissions on the local area, \(\text{firmControls}_i\) represents the control variable at the firm level, and \(\text{areaControls}_{ct}\) represents the control variable at the provincial level. \(W_{P_it}\) is the spatial lag term, which reflects the carbon emission impacts of the surrounding area on the central area. It is calculated as follows:

\[
W_{P_it} = \sum_{d=1}^{n} W_{cd}P_{dt}
\]

where \(W_{cd}\) is the inverse geographic distance spatial weight matrix established according to the latitude and longitude of the region (if the research area is at the provincial level, the matrix is \(30 \times 30\), excluding the data for Hong Kong, Macao, Taiwan, and Tibet). \(P_{dt}\) represents the carbon emissions of region \(d\) in year \(t\).

In addition to having local effects, carbon emissions may spill over to surrounding areas (the dependent variable in our study). Thus, we focus on the “spillover effect” of the local

### Table 2 Variable index and descriptive statistics results

| Variable name                   | Variable index | Mean   | Std    | Min    | Max    |
|---------------------------------|----------------|--------|--------|--------|--------|
| Carbon emission                 | lnCE           | 5.5291 | 0.7678 | 0      | 6.8170 |
| Financing costs                 | lnPRO          | 2.0736 | 0.8827 | 0      | 4.9972 |
| Firm age                        | lnAGE          | 1.9331 | 0.8693 | 0      | 3.3673 |
| Firm size                       | lnSCA          | 20.9647| 1.6056 | 7.1247 | 28.693 |
| Asset structure                 | lnSTR          | 0.3263 | 0.1357 | 0      | 0.6904 |
| GDP per capita                  | lnA            | 1.6376 | 0.6335 | 0.2071 | 3.9039 |
| Population density              | lnP            | 7.5966 | 0.6321 | 3.2581 | 8.7496 |
| Foreign direct investment       | lnFDI          | 7.0573 | 1.5249 | 1.6119 | 9.8645 |
| The proportion of secondary industry | lnT           | 3.8018 | 0.2339 | 2.9755 | 4.1352 |
| Education level                 | lnEDU          | 2.4585 | 0.6126 | 0.6202 | 5.1958 |
| Annual average temperature      | lnTEM          | 2.8285 | 0.3280 | 0      | 5.3613 |
corporate financing costs affecting carbon emissions. The model is constructed as follows:

\[
W_{pc} = \alpha_0 + \alpha_1 \ln PRO_{it} + \alpha_2 \text{firmControls}_{it} \\
+ \alpha_3 \text{areaControls}_{ct} + \lambda^c + \mu^t + \epsilon
\]  

(8)

The dependent variable is constructed as follows, representing the local spillover value of carbon emissions to the surrounding area:

\[
W_{pc} = \sum_{d=1}^{n} W_{dc}P_{ct}
\]  

(9)

where \( W_{pc} \) still represents the spatial weight matrix, but differs in the direction of influence \( P_{ct} \) represents the observed value for area \( c \) in year \( t \).

**Spatial correlation test**

We first conducted a univariate spatial correlation test. The results of the Moran index (Moran’s \( I \)) showed that in the study year, there was a significant positive spatial autocorrelation of carbon emissions in the province, meaning that the provincial carbon emissions show a significant “high–high, low–low” aggregation phenomenon. When we carried out sensitivity analysis based on the guidance provided by Anselin and Moreno (2003), the results (shown in Table 9 in the Appendix) confirmed the existence of spatial correlation.

In the global autocorrelation analysis of carbon emissions from 1998 to 2018 (see Table 3), Moran’s \( I \) was positive, and all results passed the 5% significance test. Bivariate correlation analysis can fix one-way effects in space and time. Columns (3) and (5) of Table 3 describe how the carbon emissions of a province in 2009 (2018) were affected by the weighted average carbon emissions of neighboring provinces in 1998 (2009). This interactive influence can be seen as “inward spillover.” Columns (2) and (4) show the spatial interaction effect of a province’s carbon emissions in 1998 (2009) on the weighted average carbon emissions of neighboring provinces in 2009 (2018), which can be seen as “outward spillover.”

**Analysis of empirical results**

This empirical research is divided into three parts. First, we used the fixed effects of the firm panel data to study the impacts of financing costs on local carbon emissions as the benchmark regression. Second, we studied the impacts of corporate financing costs on regional carbon emissions from the perspectives of local effect and spatial spillovers. Third, we performed robustness testing, heterogeneity testing, and endogeneity analysis.

**Estimation results for the basic model**

As shown in Table 4, we found a significant positive relationship between carbon emissions and financing costs. The regression results in columns (3) and (4) show that a 1% increase in financing costs increased regional carbon emissions by 0.0158% to 0.0165%. The regression results for the control variables were all significant at the 1% level. Specifically, we identified a significant negative correlation between greater firm age (\( \ln AGE \)) and the level of carbon emissions. Firms with a longer history have more mature emission reduction facilities and tend to engage in long-term planning, which is conducive to the realization of emission reduction targets.

The expansion of firm scale (\( \ln SAC \)) often leads to an increase in input factors such as energy, thereby increasing the production of carbon emissions. The regression results for the asset structure (\( \ln STR \)) showed that an increase in the firm’s fixed assets led to an increase in its energy consumption, which in turn increased its carbon emissions.

Per capita GDP (\( \ln A \)) had a negative relationship with carbon emissions, indicating that energy efficiency has a greater inhibitory effect on carbon emissions than does economic growth, and the “decoupling” of regional economies has achieved remarkable results. The impact of population density (\( \ln P \)) on carbon emissions was significantly negative, suggesting that the impact of population size on carbon emissions becomes weaker as the industrial structure undergoes adjustments and energy efficiency improves. An increase in the proportion of secondary industries (\( \ln T \)) with resource consumption as their main modes of production will inevitably promote a continuous increase in

**Table 3** Carbon emission global autocorrelation bivariate Moran’s \( I \) (1998–2018)

| Category         | Outward spillover | Inward spillover | Outward spillover | Inward spillover |
|------------------|------------------|------------------|------------------|------------------|
| X-axis (year)    | 1998             | 2009             | 2009             | 2018             |
| Y-axis (year)    | 2009             | 1998             | 2018             | 2009             |
| Moran’s \( I \)  | 0.291            | 0.256            | 0.256            | 0.219            |
| \( P \)-values   | 0.011            | 0.017            | 0.017            | 0.025            |
| \( Z \)-values   | 2.8762           | 2.5527           | 2.5527           | 2.1995           |
production-related carbon emissions. An increase in foreign direct investment (lnFDI) may also lead to increased carbon emissions by companies. Provinces with higher temperature (lnTEM) do not need heating in winter, so air pollution associated with heating sources is less likely; this was manifested in our results as a negative relationship between temperature and carbon emissions.

Local effects and spatial spillover analysis

After confirming the spatial correlation of carbon emissions, columns (1) and (2) in Table 5 report the use of Eq. (6) to examine the “local effects” of financing costs on carbon emissions. The estimated coefficient of financing costs on local carbon emissions was still significantly positive, indicating that an increase in financing costs led to an increase in carbon emissions. The regression coefficient of wlnCE was significantly positive, which suggests that regional carbon emissions do have significant spatial dependence. We proposed that the effects of financing costs on carbon emissions will be affected by carbon emissions in surrounding areas. The benchmark regression results actually included the externality of carbon emissions in surrounding areas. This was consistent with the regional aggregation of carbon emissions in the correlation test. In addition, the adjusted $R^2$ value was greater than that shown in Table 4, indicating that after incorporating the spatial correlation, the model better described the impacts of financing costs on regional carbon emissions.

Columns (3) and (4) in Table 5 report the use of Eq. (8) to test the “spillover effect” of carbon emissions. The results showed that financing costs had a “positive spillover effect” on carbon emissions, such that rising corporate financing costs not only increased local carbon emissions, but also created pressure to reduce emissions in surrounding areas. When the control variables (i.e., time and industry fixed effects) were added into the model, for every 1% increase in financing costs, carbon emissions from the company’s location to the surrounding area increased by about 0.0136%.

The values in brackets are standard errors; *, **, and *** are significant under the conditions of 10%, 5%, and 1%, respectively.

### Table 4 Estimated results for the basic model

| Variable | (1)          | (2)          | (3)          | (4)          |
|----------|--------------|--------------|--------------|--------------|
| lnPRO    | 0.0464***    | 0.0408***    | 0.0165***    | 0.0158***    |
|          | (0.0039)     | (0.0040)     | (0.0026)     | (0.0026)     |
| lnAGE    | −0.0262***   | −0.0217***   | −0.0160***   |              |
|          | (0.0026)     | (0.0026)     | (0.0013)     | (0.0014)     |
| lnSCA    | 0.0169***    | 0.0160***    |              |              |
|          | (0.0013)     | (0.0014)     |              |              |
| lnSTR    | 0.0920***    | 0.0987***    |              |              |
|          | (0.0153)     | (0.0164)     |              |              |
| lnA      | −0.3080***   | −0.2990***   |              |              |
|          | (0.0116)     | (0.0115)     |              |              |
| lnP      | −0.1230***   | −0.1220***   |              |              |
|          | (0.0037)     | (0.0037)     |              |              |
| lnFDI    | 0.3330***    | 0.3370***    |              |              |
|          | (0.0027)     | (0.0027)     |              |              |
| lnT      | 1.7750***    | 1.7770***    |              |              |
|          | (0.0117)     | (0.0117)     |              |              |
| lnEDU    | −0.2500***   | −0.2450***   |              |              |
|          | (0.0078)     | (0.0078)     |              |              |
| lnTEM    | −0.4350***   | −0.4240***   |              |              |
|          | (0.0073)     | (0.0073)     |              |              |
| Time effect | Yes    | Yes    | Yes    | Yes    |
| Industry effect | No    | Yes    | No    | Yes    |
| N        | 41,640       | 41,226       | 39,754       | 39,753       |
| $R^2$    | 0.255        | 0.289        | 0.765        | 0.772        |

The values in brackets are standard errors; *, **, and *** are significant under the conditions of 10%, 5%, and 1%, respectively.

### Table 5 Spatial lag model testing of the impacts of corporate financing costs on regional carbon emissions

| Variable | Local effect | Spatial spillover |
|----------|-------------|------------------|
|          | (1)         | (2)              | (3)         | (4)         |
| lnPRO    | 0.0158***   | 0.0158***        | 0.0249**    | 0.0136*     |
|          | (0.0025)    | (0.0026)         | (0.0079)    | (0.0045)    |
| wnCE     | 0.0853***   | 0.0843***        |              |              |
|          | (0.0019)    | (0.0019)         |              |              |
| lnAGE    | −0.0173***  | −0.0136***       | −0.1500***  | −0.1360***  |
|          | (0.0025)    | (0.0026)         | (0.0079)    | (0.0080)    |
| lnSale   | 0.0122***   | 0.0113***        | 0.0655**    | 0.0667***   |
|          | (0.0013)    | (0.0014)         | (0.0039)    | (0.0042)    |
| lnSTR    | 0.0906***   | 0.0929***        | 0.1510**    | 0.2290***   |
|          | (0.0149)    | (0.0160)         | (0.0468)    | (0.0497)    |
| lnA      | −0.2850***  | −0.2780***       | −0.4300***  | −0.3910***  |
|          | (0.0113)    | (0.0112)         | (0.0354)    | (0.0347)    |
| lnP      | −0.1010***  | −0.1010***       | −0.4310***  | −0.4170***  |
|          | (0.0036)    | (0.0036)         | (0.0113)    | (0.0111)    |
| lnFDI    | 0.3330***   | 0.3370***        | 0.3090***   | 0.3070***   |
|          | (0.0026)    | (0.0026)         | (0.0081)    | (0.0081)    |
| lnT      | 1.7250***   | 1.7340***        | 2.6440***   | 2.5560***   |
|          | (0.0114)    | (0.0114)         | (0.0356)    | (0.0353)    |
| lnEDU    | −0.3320***  | −0.3260***       | 0.4920***   | 0.4960***   |
|          | (0.0078)    | (0.0078)         | (0.0238)    | (0.0234)    |
| lnTEM    | −0.4710***  | −0.4610***       | 0.1280***   | 0.1540***   |
|          | (0.0072)    | (0.0072)         | (0.0222)    | (0.0220)    |
| Time effect | Yes    | Yes    | Yes    | Yes    |
| Industry effect | No    | Yes    | No    | Yes    |
| N        | 39,754      | 39,753          | 39,754      | 39,753      |
| $R^2$    | 0.777       | 0.783           | 0.332       | 0.364       |

The values in brackets are standard errors; *, **, and *** are significant under the conditions of 10%, 5%, and 1%, respectively.
levels and policy regulations in the various regions, the “spillover effect” of financing costs on carbon emissions was slightly smaller than the “local effect.”

**Robustness tests**

As shown in Tables 4 and 5, when we controlled for the industry fixed effects, the regression coefficient of the core explanatory variables decreased, or even decreased significantly; this suggests that the impacts of financing costs on carbon emissions may tend to aggregate within a specific industry. Table 6 shows that the results were still robust when we excluded industries with higher financing costs from the regression. In addition, the significance and coefficient of the variables increased significantly, indicating that there were industry differences in the positive correlation between corporate financing costs and carbon emissions.

We also considered whether the spatial weight matrix using geographic proximity might be affected by the number of neighbors—that is, the smaller the number of neighbors, the greater the influence of each neighbor. If there is only one neighbor, even if data are normalized, all of the weights will be assigned to this neighbor. Notably, in the context of our study, the area of the provincial administrative regions in the western region of China is larger than the area of the eastern provincial administrative regions. Using the radius distance spatial weight matrix would therefore result in too many neighbors in the eastern provincial administrative regions. To account for this factor, we changed the threshold distance to use the K-order adjacent neighbors, the greater the influence of each neighbor. If there is only one neighbor, even if data are normalized, all of the weights will be assigned to this neighbor. Notably, in the context of our study, the area of the provincial administrative regions in the western region of China is larger than the area of the eastern provincial administrative regions. Using the radius distance spatial weight matrix would therefore result in too many neighbors in the eastern provincial administrative regions. To account for this factor, we changed the threshold distance to use the K-order adjacent neighbors, the greater the influence of each neighbor. If there is only one neighbor, even if data are normalized, all of the weights will be assigned to this neighbor.

**Heterogeneity tests**

The decoupling index reflects the differences in the transformation of the economic structures in different regions. Based on the Tapio decoupling index we calculated earlier, we divided the study provinces into two samples: those with weak decoupling and those with expansive coupling. The estimation results in Table 7 show that regions in the state of “weak decoupling” exhibited a stronger positive effect of financing costs on carbon emissions, while regions in the “expansive coupling” sample showed the opposite (and insignificant) effect.

Regions in the “expansive coupling” sample included Inner Mongolia, Ningxia, and Xinjiang. These regions rely more on agriculture, animal husbandry, and other industries for economic development. Their financial markets are not perfect, and their economic growth and carbon emission growth are basically synchronized. Therefore, the impacts of financing costs on carbon emissions were not obvious in this sample.

### Table 7 Heterogeneity tests based on decoupling state

| Variable | Weak decoupling area | Expansive coupling area |
|----------|----------------------|-------------------------|
|          | Local effect | Spatial spillover | Local effect | Spatial spillover |
| lnPRO    | 0.0170*** | 0.0225** | −0.0111 | −0.0214 |
| (0.0023) | (0.0075) | (0.0259) | (0.0488) |
| whnCE    | 0.1510*** | 0.495** | 0.1540*** | 0.0449 |
| (0.0019) | (0.0250) | (0.0290) | (0.0449) |
| lnAGE    | −0.0050' | −0.1490*** | −0.0013 | 0.1540*** |
| (0.0023) | (0.0075) | (0.0250) | (0.0449) |
| lnSale   | 0.0074*** | 0.0648*** | −0.0225 | −0.0396 |
| (0.0012) | (0.0039) | (0.0127) | (0.0198) |
| lnSTR    | 0.0628*** | 0.3040*** | 0.2730* | 0.0903 |
| (0.0145) | (0.0469) | (0.1350) | (0.2100) |
| lnA      | −0.3440*** | −0.1200*** | 1.2890*** | 6.4980*** |
| (0.0102) | (0.0330) | (0.2530) | (0.3500) |
| lnP      | −0.0880*** | −0.5320*** | −0.1820*** | 0.0364 |
| (0.0035) | (0.0112) | (0.0254) | (0.0390) |
| lnFDI    | 0.3780*** | 0.1080*** | 0.3220*** | 0.8370*** |
| (0.0025) | (0.0080) | (0.0453) | (0.0666) |
| lnT      | 1.6320*** | 2.9520*** | −5.1200*** | −3.5670*** |
| (0.0105) | (0.0334) | (0.3930) | (0.6110) |
| lnEDU    | −0.3990*** | 0.6340*** | −0.6170*** | −2.6720*** |
| (0.0071) | (0.0220) | (0.1560) | (0.2270) |
| lnTEM    | −0.4120*** | 0.0642** | −2.9300*** | 4.9690*** |
| (0.0064) | (0.0207) | (0.3150) | (0.3990) |
| N        | 38,412 | 38,412 | 1340 | 1340 |
| $R^2$    | 0.821 | 0.375 | 0.822 | 0.839 |

The values in brackets are standard errors; ‘*’, ‘**’, and ‘***’ are significant under the conditions of 10%, 5%, and 1%, respectively
Regions in the “weak decoupling” sample had achieved remarkable results in reducing emissions. At the same time, the impacts of financing costs on their local carbon emissions were significant at the 1% level. When their financing costs increased by 1%, the impacts of local carbon emissions increased by 0.017%. Carbon emission spillover to the surrounding areas increased by about 0.0225% under this condition, a growth level higher than that seen in the benchmark regression. Thus, reducing the financing costs of firms in such areas promises to bring about a significant enhancement of the emission reduction effect.

**Endogenous analysis**

The higher carbon emissions of firms may affect those enterprises’ financing costs, though this research mainly considers the endogeneity problem that may be brought about by mutual cause and effect. For example, companies that emit more carbon dioxide may face administrative penalties, including fines. Such fines become part of the company’s costs. When information asymmetry is present, investors will reduce their investments in such companies, making it difficult for companies to obtain financing. When selecting the instrumental variables for endogenous treatment, we noted that local governments will support firms’ emission reduction actions. If companies are actively seeking to reduce their carbon emissions, the government will tend to view them favorably—and may pass on this positive information to potential financing sources. Thus, having a good reputation can help companies obtain more bank credit and reduce their financing pressure.

Although bank lending does not directly affect local carbon emissions, it is a relatively good exogenous policy tool variable. Table 8 reports the empirical results after controlling for the endogeneity of bank credit at the end of each year. In essence, these data confirmed the robustness of our earlier results.

**Discussion**

Countries around the world and international social organizations alike have promoted the signing of a number of climate change–related agreements, driving the financial industry to gradually develop financing services to support carbon reduction. So, how will financing costs affect the results of carbon emissions?

First, we found that raising financing costs increases carbon emissions. Enterprises not only represent the demand side of funds, but also serve as the main drivers in green technology development. Financing costs affect corporate behavior, with that behavior reflecting the size of the environmental impacts that green funds can ultimately achieve (MacAskill et al. 2021). If the financing cost of enterprises is appropriately reduced, it will help the enterprises to internalize the costs of carbon emissions, on the one hand, and to obtain more capital investment for their preliminary green projects, on the other hand. Thus, lower financing costs will encourage the enterprises to actively carry out green technology research and development to ensure they can achieve carbon reduction and improve environmental quality (Bolton et al. 2020).

In addition, spatial economics asserts that there is a correlation between the economic geographic behavior of a spatial unit and the behavior of neighboring regions, which incorporates a certain degree of spatial dependence and correlation characteristics. Kang et al. (2016) have suggested that there are obvious spatial spillover effects of carbon emissions in China’s provinces, and that ignoring the spatial factors will lead to wrong estimations of this model. Our research is the first to consider the inter-provincial transfer of carbon emissions in the study of the impact of corporate financing costs on regional carbon emissions. Our spatial autocorrelation analysis showed that there is, indeed, an obvious “agglomeration effect” in carbon emissions. Differing from the approach taken in the related literature, we specifically divided the spatial effect into two aspects—the impact on the local area and the impact on the surrounding area—which is similar to the direct effect and the indirect effect proposed by LeSage and Pace (2009). The spatial effect may have a time lag, so we took the time factor into account in the spatial correlation analysis and used a bivariate correlation analysis to fix the one-way effect in the space–time effect. This analysis revealed that raising financing costs increases carbon emissions, both locally and in the surrounding area.

On the one hand, high financing costs have created a threshold effect in regard to carbon emissions (Tamazian et al. 2009), such that only large-scale enterprises can afford the financing risks and use funds for carbon reduction activities. Enterprises that reject high financing costs have small production scales, imperfect supporting facilities, and production activities that are usually accompanied by high carbon emissions. On the other hand, adjustments in carbon emissions based on financial funding need to be matched with adjustments in industrial structure. Only by helping enterprises to promote

| Table 8 Instrumental variable regression |
|-------------------------------|-----------------|---------------|-----------------|
| Variable | IV regression results | Local effect | Spatial spillover |
| lnPRO | 0.158*** | 0.104*** | 0.729*** |
| (0.0376) | (0.0356) | (0.120) |
| whnCE | 0.0931*** | 0.0931*** | 0.120*** |
| (0.00203) | (0.00203) | (0.00203) |
| Constant | −0.662*** | −0.700*** | −5.717*** |
| (0.0733) | (0.0698) | (0.234) |

1%, 5%, and 10% significance levels are highlighted by ***, **, and *, sequentially.
the development of low-carbon industries can the low-carbon effect of financing be guaranteed (Hammond and Norman 2012).

Our results also suggested that lowering financing costs has a greater effect on local carbon reduction than on carbon reduction in surrounding areas. The scale of the economy, the speed of development, and the intensity of environmental regulation differ for each province, and all of these factors may, in turn, affect carbon emissions. Therefore, local adjustment of financing costs is needed to coordinate and work with other factors to achieve carbon emission targets. However, most of the surrounding areas are only affected by carbon emission spillover, so the degree of impact is small.

Finally, we relied on the “decoupling” indicator to measure the relative speed of economic development and carbon emissions. Our findings indicated that the difference in “decoupling” between provinces had increased over time. Most provinces switched from “weak decoupling” or “expansive coupling” to “weak decoupling” over the study period, a result consistent with Gao et al. (2021). Unlike similar studies, our research included a regression of samples based on different “decoupling” states, with the results showing that it is more effective to carry out carbon reduction activities by reducing corporate financing costs in areas with obvious “decoupling.” This conclusion is consistent with the actual development of China’s economy. On the one hand, China’s provincial-level regions have large differences in area and population; on the other hand, due to the slow industrialization process of the less-developed provinces in western China, carbon emissions are relatively low there. By comparison, the eastern provinces have geographic advantages and have realized dividends from the national carbon reduction policy, and their economic development started earlier, resulting in a large amount of carbon emissions during the development process. In these provinces, firms tend to find it more beneficial to carry out targeted carbon reduction activities (Hu et al. 2017).

Conclusions, policy implications, and limitations

Conclusions

Across the world, shocks such as global warming, environmental pollution, and energy consumption ultimately affect all financial market participants and individual investors (Sharif et al. 2020). Corporate financing behavior in financial markets is also closely related to regional carbon emissions. This study used data from Chinese listed companies to refine the research on carbon emissions on the microlevel, established a panel fixed effect model and a spatial lag regression model, and empirically analyzed the impacts of corporate financing costs on regional carbon emissions. The results yielded three important lessons.

First, an increase in corporate financing costs will increase regional carbon emissions. Firm age, firm scale, asset structure at the firm level, economic development level, economic structure, foreign direct investment level, population density, environmental climate, population quality, and other factors at the regional level have significant effects on regional carbon emissions at the statistical level.

Second, after incorporating the spatial factor, it appears that the effects of corporate financing costs on carbon emissions in the local region are subject to the “spillover” of carbon emissions in the surrounding areas (local effect), and an increase in carbon emissions in the local region will also “spillover” to the surrounding areas (spillover effect). The role of the “local effect” is greater than that of the “spillover effect.”

Third, the “local effects” and “spillover effects” in “weak decoupling” regions are significantly greater than those in “expansive coupling” regions. In other words, reducing the financing costs of firms in “weak decoupling” regions can achieve more significant carbon reduction outcomes.

Policy implications

Based on the preceding conclusions, the following suggestions are put forward. First, to achieve carbon reduction goals, it is important to reduce financing costs for firms that seek to carry out low-carbon activities. It is also recommended to improve the adaptability of corporate financing and corporate low-carbon practices. Vigorously reducing the financing costs of firms, especially by providing more complete financing channels for firms that carry out environmental governance, pollution reduction, and carbon reduction efforts, and effectively dealing with problems such as information asymmetry in the financial trading market will enhance the likelihood of reaching the desired emission levels.

Second, governments and enterprises need to build a spatial linkage mechanism that supports regional carbon reduction. Areas with serious carbon emissions should effectively cut off the sources of carbon emissions based on traceability analyses, while simultaneously aiming to avoid asymmetry between carbon emission rights and carbon reduction responsibilities. The significant inter-provincial transfer of carbon emissions highlights that achieving carbon reduction goals will require multiregional coordination, and specific carbon reduction targets should be formulated according to the economic development status of different regions.

Finally, measures to reduce regional carbon emissions by reducing corporate financing costs should be implemented mainly in “weak decoupling” regions. Our empirical analysis results indicate that reducing the financing costs of firms in “weak decoupling” areas can effectively avoid hindering
the economic growth of firms that undertake carbon reduction efforts while still reducing overall carbon emissions. Therefore, reducing financing costs in “weak decoupling” regions can achieve a win–win goal—reducing carbon emissions while still supporting economic growth.

**Limitations**

This study, like all research, has some shortcomings. First, the impact of the COVID-19 pandemic on the study’s conclusions was not considered. The pandemic has had a huge impact not just on the global economy, but also on financial market activities (Sharif et al. 2020). Measuring global economic policy uncertainty showed that these perceived uncertainties may affect consumption and investment, thereby reducing the overall scale of economic activity (Işık et al. 2020). This may have some influence on the conclusions of this study. Of course, the publication of data takes time, and relevant data for the pandemic period were not available during the research phase of the study. Moreover, if such data had been available and were combined with the annual data for non-pandemic years, it would inevitably lead to biased estimates. Thus, follow-up studies should consider updating the content of the data and adopt causal identification methods such as differences-in-differences (DID) analysis to eliminate the impacts of the pandemic and other factors before conducting research.

In addition, we constructed the spatial weight matrix only from the perspective of geographic proximity. In reality, the correlation between regions has complex associations. Future research might consider constructing a spatial weight matrix based on economic distance and other aspects—that is, assigning greater weights to spatial units with similar levels of economic development—so as to more accurately describe the relationship between spatial units.

**Appendix**

**Table 9** Significance of permutation tests

| Category | 99 permutations       | 199 permutations | 999 permutations |
|----------|-----------------------|------------------|------------------|
| X: 1998; Y: 2009 | 0.020                 | 0.015            | 0.007            |
| X: 2009; Y: 1998 | 0.030                 | 0.010            | 0.018            |
| X: 2009; Y: 2018 | 0.010                 | 0.020            | 0.014            |
| X: 2018; Y: 2009 | 0.030                 | 0.025            | 0.042            |

**Table 10** Regression results after replacing the spatial weight matrix

| Variable | Local effect | Spatial spillover |
|----------|--------------|-------------------|
|          | (1)          | (2)               | (3)               | (4)               |
| lnPRO    | 0.0115**     | 0.0112***         | 0.0261***         | 0.0234***         |
|          | (0.00247)    | (0.00252)         | (0.00409)         | (0.00413)         |
| winCE    | 0.191***     | 0.194***          |                   |                   |
|          | (0.00303)    | (0.00305)         |                   |                   |
| lnAGE    | −0.0228***   | −0.0189***        | −0.0180***        | −0.0144***        |
|          | (0.00247)    | (0.00252)         | (0.00409)         | (0.00414)         |
| lnSale   | 0.0101***    | 0.00891***        | 0.0355***         | 0.035***          |
|          | (0.00123)    | (0.00132)         | (0.00204)         | (0.00216)         |
| lnSTR    | 0.0959***    | 0.0994***         | −0.0208           | −0.00347          |
|          | (0.0146)     | (0.0157)          | (0.0242)          | (0.0258)          |
| lnA      | −0.342***    | −0.335***         | 0.174***          | 0.187***          |
|          | (0.0111)     | (0.0109)          | (0.0183)          | (0.0180)          |
| lnP      | −0.106***    | −0.106***         | −0.0855**         | −0.0805**         |
|          | (0.00354)    | (0.00352)         | (0.00585)         | (0.00577)         |
| lnFDI    | 0.319***     | 0.323***          | 0.0740***         | 0.0702***         |
|          | (0.00255)    | (0.00255)         | (0.00421)         | (0.00418)         |
| lnT      | 1.469***     | 1.473***          | 1.600***          | 1.564***          |
|          | (0.0121)     | (0.0121)          | (0.0184)          | (0.0183)          |
| lnEDU    | −0.347***    | −0.342***         | 0.506***          | 0.498***          |
|          | (0.00758)    | (0.00754)         | (0.0123)          | (0.0121)          |
| lnTEM    | −0.346***    | −0.336***         | −0.465***         | −0.454***         |
|          | (0.00709)    | (0.00707)         | (0.0115)          | (0.0114)          |

| Time effect | Yes | Yes | Yes | Yes |
| Industry effect | No | Yes | No | Yes |
| N           | 39,754 | 39,753 | 39,754 | 39,753 |
| R²          | 0.786 | 0.793 | 0.481 | 0.505 |

The values in brackets are standard errors; *, **, and *** are significant under the conditions of 10%, 5%, and 1%, respectively.

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

**Declarations**

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