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Strategic interactions for carbon emissions in Chinese cities are influenced by mayors

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City-related mitigation measures are crucial for reducing carbon emissions, but most studies on this issue treat cities as independent entities and neglect their interactions. This is especially relevant in the Chinese context, where peers influence policy decisions. Here we offer a novel perspective about mayors' strategic interactions to explain cities' carbon intensity reduction. We use a spatial Durbin model to investigate the effects and patterns of interaction on carbon intensity among Chinese cities from 2000 to 2019. We found that mayors' interaction impacted cities' carbon intensity, resulting in a 0.792% reduction in reference cities for every 1% decrease in neighboring cities. Mayors with higher education, younger ages, science-related majors and working in their hometowns had better performance. Additionally, we revealed an 'imitation competition' pattern (emulating the practices of the neighboring cities). This study offers new insights into city emissions policies and introduces new recommendations.

Cities are responsible for 70% of global carbon emissions from energy consumption[1]. In China, depending on the definition of emissions scope and accounting methodology, this proportion can reach up to 85% (ref. 2), which is much higher than that of the United States (80%) or Europe (69%)[3]. China was responsible for 28% of global energy-related carbon emissions in 2019 (ref. 4). Therefore, the international community has closely monitored China's commitment to peak carbon by 2030 and achieve carbon neutrality by 2060 ('3060' goals)[5]. In this context, city-related mitigation measures are crucial to China's efforts to reduce carbon emissions.

China has made notable progress in addressing climate change, which can be attributed to its political and economic system. The central government delegates considerable power to local governments to implement environmental regulations, which has resulted in effective environmental decentralization. The Chinese-style Performance Appraisal System incentivizes mayors to commit to emissions mitigation by linking career prospects to their jurisdiction's mitigation performance, creating political centralization. This approach has resulted in a 'yardstick competition' among mayors to seize opportunities for promotion under environmental decentralization and political centralization (Part A.1 in Supplementary Information). Behavior is interrelated because peers' actions can affect the political and market environment in which local policy decisions are made[6]. Some evidence suggests that cities' decision-making is not independent but is instead influenced by their peers. For instance, local governments may rush to adopt lower environmental standards to attract foreign investments[7]. Therefore, horizontal interaction is crucial to comprehending the public sector equilibrium in carbon emission reductions.

The trans-regional cooperation system in China aims to mobilize and reshape horizontal competition. For instance, the Counterpart Assistance System encourages developed cities to support cities in border and ethnic areas, the construction of major national projects areas, the Northeast Region, and emergency and disaster relief areas (many-to-one/many-to-many pattern), to address the problem of uneven regional development[8]. Therefore, inter-city linkage is not limited to a certain geographical range.

Academia has investigated the relationship between government and the reduction of carbon emissions. Previous scholars have analyzed the effectiveness of government regulations on the market entities[9–11]. The principal-agent theory was developed to explain situations where market mechanisms cannot predict the behavior of authorities. However, scholars have suggested that the behavioral logic behind China's ecological and environmental regulations should be carefully examined, given China's unique political and economic system. Scholars have developed theories to explain the effects of carbon emission, including incentive compatibility, promotion tournaments and yardstick competition in both vertical and horizontal relations[12–14]. For instance, according to Kahn et al.[15], changes in political promotion

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rules by the central government created an incentive for local authorities to reduce border pollution. Regarding horizontal relations, local authorities adjusted their behavior based on their neighbors, resulting in various interaction patterns such as 'race to the top' (competing to achieve carbon reduction target) and 'race to the bottom' (following neighboring areas' behavior to ignore carbon regulation)[16,17].

These studies have contributed to the existing knowledge by introducing government behavior and enhancing our understanding of environmental governance. Although some studies have analyzed horizontal strategic interactions of environmental regulation, they mainly focus on water and air pollution (Table C1 in Supplementary Information)[18–20]. The relevant studies do not apply to a broader spatial scope of strategic interactions. Pollution externalities are limited in a specific spatial scope and are highly dependent on geographical conditions. This implies that intergovernmental interactions are localized. Pollution-based interactions are more evident in geographically adjacent cities within the same province, or that share a common administrative boundary. However, these studies cannot explain the global scope of carbon-based interaction. Additionally, the role of decision-makers has not been thoroughly investigated.

In this article, we applied a spatial Durbin model (SDM) to address these gaps using data from 284 Chinese cities between 2000 and 2019. The results of this study contribute to the existing literature in two ways. First, this paper presents a spatial perspective on explaining carbon intensity reduction in cities through horizontal strategic interactions. This supplements and enhances our understanding of cities' behavior and creates appropriate policy instruments for city management. Second, we uncover the following finding: mayors who are younger, have higher education levels, with science-related backgrounds, and work in their hometowns are significantly associated with greater reductions in carbon intensity. This suggests that mayors play a crucial role in combating climate change.

Results

Mayor's strategic interaction effect on carbon emissions

Our first objective was to investigate the effects of strategic interaction on carbon intensity. The statistical tests, including the spatial autocorrelation tests, likelihood ratio (LR) test and Wald tests, support the SDM model (Tables E1 and E2 in Supplementary Information). Table 1 presents the strategic interaction effects between cities using four different spatial weight matrices $\mathbf{W}_1$-$\mathbf{W}_4$: geospatial distance matrix, economic distance matrix, economic and geospatial distance-weighted matrix and administrative distance matrix, respectively (see Table D2 in Supplementary Information for the weight matrix settings). The estimated coefficients ρ of the four spatial weight matrices are significantly greater than 0, indicating a positive interaction effect of carbon intensity between cities. In the 'benchmark competition' pattern, local cities will follow suit when their neighbors reduce their carbon intensity, supporting hypothesis 1 in Part A.2 of Supplementary Information. In terms of the magnitude of the interaction effect, the effects of the economic distance- and geospatial distance-weighted matrix (0.792) are larger than those of the administrative (0.678) and economic (0.071) distance-weighted matrices, but smaller than those of the geographical distance-weighted matrix (2.657). Accordingly, this study highlights pronounced strategic interactions between economically and geospatially related cities. The economic and geospatial distance-weighted matrix ($\mathbf{W}_3$) was used in the subsequent analysis. The indicator offers a comprehensive view of the intricate relationships between local governments. Geographically adjacent cities share similar natural conditions and development levels, resulting in closely linked interests. In addition, cities are economically interconnected through 'GDP-oriented' promotion tournaments, counterpart systems and competition for mobile resources. Therefore, a single matrix such as $\mathbf{W}_1$ cannot fully capture the horizontal interactions between local governments. Moreover, a higher value for $\mathbf{W}_1$ would lead to overestimating the results. On the other hand, $\mathbf{W}_3$, which falls within the range of maximum and minimum values, is a more reasonable option. The robust test results are shown in Part E.3 in Supplementary Information.

Table 1 | SDM results under the four weight matrices

	$\mathbf{W}_1$	$\mathbf{W}_2$	$\mathbf{W}_3$	$\mathbf{W}_4$
Neighbor effect (ρ)	2.657***	0.071**	0.792***	0.678***
	(0.030)	(0.028)	(0.021)	(0.010)
Control variable	Yes	Yes	Yes	Yes
Spatial fixed effect	Yes	Yes	Yes	Yes
Hausman test	4,226.93***	522.59***	143.38***	623.88***
Wald test for SAR	230.04***	103.53***	172.43***	289.61***
Wald test for SEM	129.49***	103.95***	181.23***	205.38***
LR test for SAR	430.95***	102.58***	162.34***	284.92***
LR test for SEM	−76.67	102.99***	138.18***	201.52***
Observations	5,680	5,680	5,680	5,680
R^2	0.104	0.045	0.040	0.008

Note: Table 1 presents the parameter estimation results using the maximum likelihood approach. The LR tests and Wald tests indicate that the SDM is suitable. The fixed effect model is suitable as the Hausman test result is significant at the 1% level. 'Yes' denotes that the control variable and spatial fixed effect are controlled in the model. The standard error is shown in parentheses. ***$P<0.01$, **$P<0.05$, *$P<0.1$. P values are for a two-sided test based on normal distribution.

Heterogeneity analysis of mayors' strategic interactions

This study conducted the heterogeneity analysis of the strategic interaction effect, considering the spatial, temporal and urban differences (see the method in Part D.1 in Supplementary Information).

We examined the two identified characteristics to investigate the spatial heterogeneity of the strategic interaction effect on carbon intensity, as illustrated in Fig. 1a. The study found that the strategic interaction effect positively impacts cities within 1,400 km, while not for cities beyond this distance. This indicates that the interaction effect has a geographical threshold. The results suggest that strategic interaction behavior extends beyond provincial administrative boundaries to encompass a national scale. This may be related to China's interregional counterpart assistance and cooperation programs. Moreover, it shows that the strategic interaction effect increases and decreases as geographical distance increases, peaking at a radius of 400 km with a value of 0.708. This suggests that the most intense strategic interaction occurs within 400 km, usually within provincial boundaries. Therefore, it is crucial to consider the scope of the strategic interaction effect in the context of carbon regulation.

The interaction effects of five-year plans (FYPs) may vary due to distinct characteristics that shape national objectives and challenges. Figure 1b illustrates the impact of strategic interaction on carbon intensity in each FYP. The 95% confidence interval indicates a significant difference from 0 for the coefficients. The interaction effects on carbon intensity showed an increasing trend, indicating increased attention toward neighboring cities' carbon regulations. During the 10th FYP, the average effect value was 0.689, suggesting that for each 1% increase in the carbon intensity of neighboring cities, the carbon intensity of local cities increases by 0.689%. However, during the 11th FYP, the interaction effect decreased slightly (0.681). Local governments' interactive behavior was closely related to central government incentives. The more ambitious the central government pursued, the greater the effort local governments would make to recalibrate their competitive behavior. During the 12th FYP, the national development strategy included a binding target of reducing carbon intensity by 17% for the first time. This target has been strengthened in subsequent FYPs to demonstrate the central government's commitment. As a result, intergovernmental

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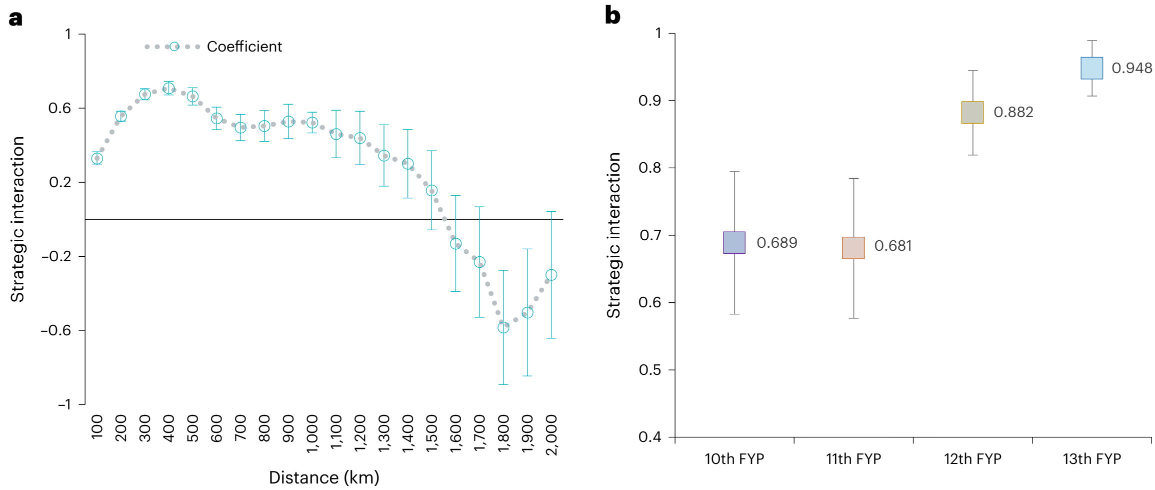

Fig. 1 | Heterogeneity analysis of spatio-temporal interaction effects. a, Effect on different distances. The gray dotted line is the mean of interaction coefficient. The solid blue line indicates the 95% confidence interval. **b**, Effect on different FYPs. The squares are the mean of interaction coefficients. The line from top to bottom of each bar represents the 95% confidence interval. The sample size is 1,420 for each FYP. *P* values of the four group is 7.858×10^{-35}, 2.223×10^{-35}, 7.006×10^{-134} and 4.124×10^{-264}, respectively.

strategic interaction has significantly increased, driven by the mobilization of political resources to respond to the performance system reform of party and government cadres and the national campaign on carbon control. The average level of strategic interaction reached 0.882 from 2011 to 2015 and 0.948 from 2016 to 2019.

We also examine whether there are any differences between the low-carbon pilot cities and the nonpilot cities. China has implemented three rounds of Low Carbon City Pilot programs in 2010, 2012 and 2017 (for more details, see Part B of Supplementary Information). During these programs, cities were required to adhere to more stringent carbon intensity constraints[21]. Therefore, analyzing the interaction effects between low-carbon pilot and nonpilot cities is particularly important. Figure 2a compares the average effect of strategic interaction between pilot and nonpilot cities. The strategic interaction coefficient of pilot cities is 0.761, smaller than that of nonpilot cities (1.011), and differences between groups are statistically significant.

To assess cities' carbon intensity reduction performance, it is crucial to analyze the strategic interaction effects of cities under different competitive pressures. Therefore, we divided the cities into two groups based on their carbon intensity rankings—the top 50% and bottom 50%—and considered the latter facing greater pressure. Figure 2b shows a statistically significant strategic interaction coefficient of 0.502 for the top 50% of cities. For cities in the bottom 50%, the strategic interaction coefficient is 0.700, which is 0.198 higher than the coefficient for cities in the top 50%. The differences between groups are statistically significant. In other words, cities falling behind in reducing their carbon intensity are more likely to respond to the performance of neighboring cities under great pressure to control carbon emissions.

China's frequent cadre turnover facilitates local officials' compliance with central directives, enabling the central government to supervise and control them[22]. The system has recently incorporated auxiliary goals related to cadre training, policy dissemination and bridging administrative gaps[23,24]. China's leadership attaches considerable importance to cadre turnover. However, few studies have assessed whether this system is functional in carbon regulation. We investigated whether the cadre turnover system affected the strategic interaction effect on carbon intensity between cities. The results are shown in Fig. 2c. The coefficient of the turnover year is statistically significant (0.785), while coefficient of the noncadre turnover year is not. The significant difference between turnover years and nonturnover years in implementing state-led carbon reduction initiatives may be due to cadre turnover motivating mayors to reduce emissions. This is also known as the proverbial 'A new official applies strict measures'.

The political system centralizes carbon peaking targets to evaluate local governments, fostering political competition between mayors to reduce carbon emissions. As a result, local governments' target setting inevitably takes into account those of superior and peer-level governments. The carbon peaking targets are positively correlated with local governments' peak carbon pressure. Local governments sometimes set higher peak carbon targets than the national target to express their ambitions, which can result in increased carbon peaking pressure. Conversely, some conservatives follow or set lower carbon peaking targets after balancing economic growth and carbon intensity reduction, resulting in decreased peaking pressure. Figure 2d illustrates the differences in the interaction effect of carbon peaking pressures in various regions. It reports a statistically significant strategic interaction coefficient of 0.784 for cities with higher carbon peaking pressures, and the coefficient for cities with relatively lower pressures is 0.026 lower. The differences between the two groups were not statistically significant. This suggests that carbon peaking pressures incentivize interactions between mayors with little variation between regions.

Mayors' strategic interaction patterns

This study used the two-regime SDM to analyze the strategic interaction patterns in carbon regulations. Figure 3 shows the estimated coefficients of δ_1 and δ_2 based on the three different spatial matrices. The outcome for $\mathbf{W}_2$ was eliminated because most coefficients were insignificant. The results indicate an 'imitative competition' pattern, where city *i* will follow suit when neighboring cities increase or decrease their carbon intensity, thus verifying hypothesis 2 in Part A.2 of Supplementary Information. In summary, local governments have the option to either compete to reduce carbon intensity ('race to the top') or follow neighboring areas' behavior and ignore carbon intensity control ('race to the bottom') to balance their gross domestic product (GDP) and other objectives. The study also suggests that both low- and high-level equilibrium can coexist. Moreover, in the 'imitative competition' pattern, stronger entities tend to imitate weaker ones, as the difference between the coefficients of δ_1 is significantly smaller than δ_2. For instance, when considering the spatial weight matrix $\mathbf{W}_3$, δ_2 is significantly larger than δ_1 by 0.164 in condition d_1 and 0.055 in condition d_2, respectively. This suggests that, for city *i*, the impact of neighboring cities with higher carbon intensity is considerably greater than those with lower carbon

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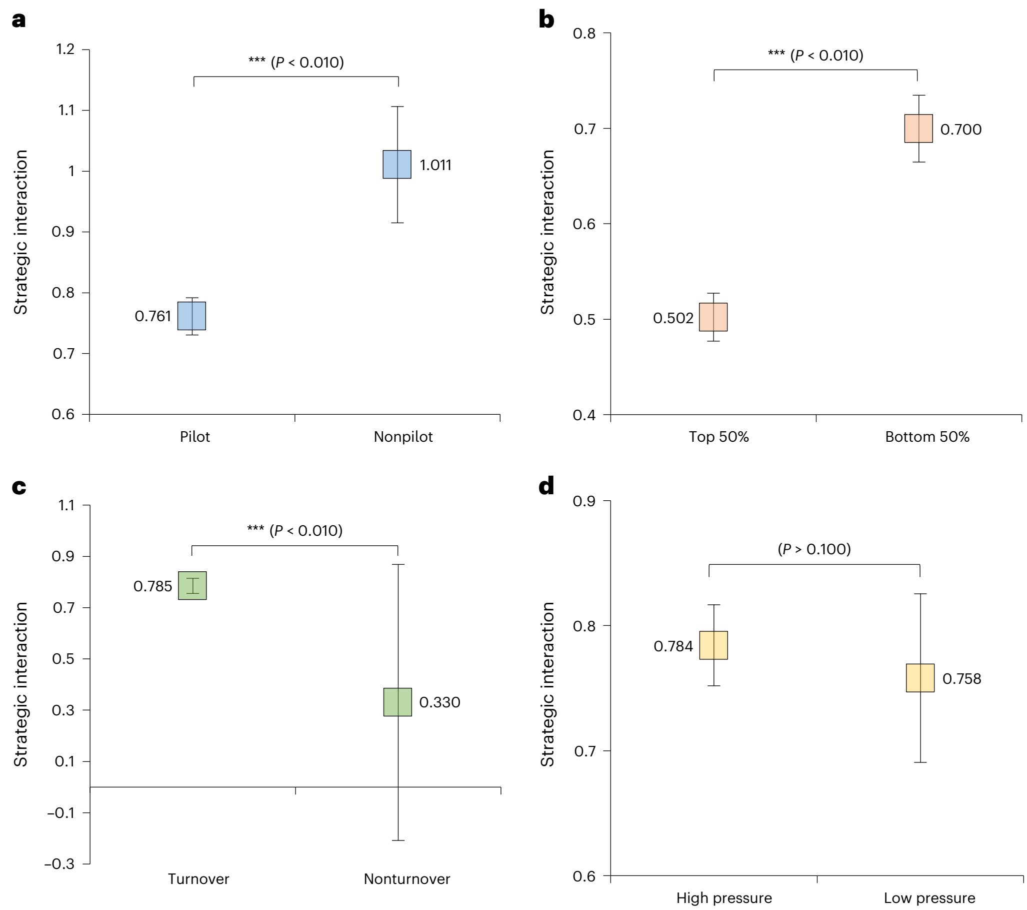

Fig. 2 | Heterogeneity analysis of strategic interaction between different cities. The squares are the mean of interaction coefficients. The solid black line indicates the 95% confidence interval. The asterisks indicate the significance degree of between-group variation (***$P < 0.010$, **$P < 0.050$, *$P < 0.100$). A two-sided t-test is used for between-group variation comparison. **a**, Interaction effect on pilot and nonpilot cities. The sample size is 367 and 5,313 in the pilot group and the nonpilot group, respectively. P values between the pilot group and the nonpilot group is 1.36×10^{-6}. **b**, Interaction effect on top 50% of cities and bottom 50% of cities. The sample size is 2,840 and 2,840 in top 50% group and bottom 50% group, respectively. P values between pilot group and nonpilot group is 4.7×10^{-8}. **c**, Interaction effect on cadre turnover and nonturnover years. The sample size is 1,645 and 4,035 in the turnover group and the nonturnover group, respectively. P values between the pilot group and the nonpilot group is 0.099. **d**, Interaction effect on high-pressure and low-pressure cities. The sample size is 1,120 and 4,560 in the high-pressure group and the low-pressure group, respectively. P values between the pilot group and the nonpilot group is 0.483.

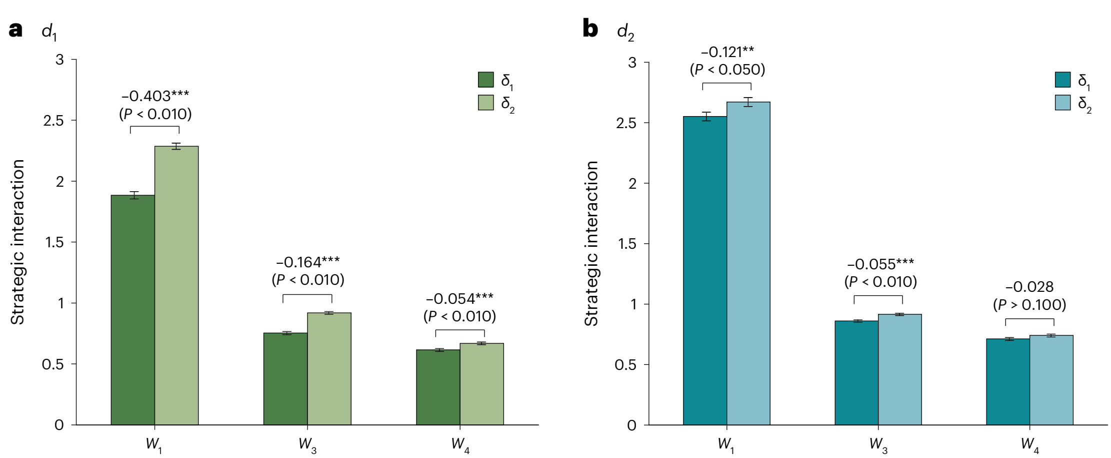

Fig. 3 | Histogram of the strategic interaction patterns in carbon regulations. **a**, Strategic interaction pattern in condition d_1. The sample size is 3,150 for δ_1 and 2,530 for δ_2 in condition d_1. **b**, Strategic interaction pattern in condition d_2. The sample size is 2,796 for δ_1 and 2,884 for δ_2 in condition d_2. The LR tests and Wald tests are used for model selection. The height of the bar is the mean of interaction coefficients. The solid black line indicates the 95% confidence interval. The value is between-group variation, and asterisks indicate the significance degree of between-group variation (***$P < 0.010$, **$P < 0.050$, *$P < 0.100$). A two-sided t-test is used for between-group variation comparison.

Table 2 | Direct and indirect effects of SDM under W_3

Direct effect			Indirect effect		
Education	**−0.005***	**(0.003)**	**w×Education**	**−0.071**	**(0.053)**
Major	−0.015**	(0.004)	w × Major	−0.156**	(0.077)
Tenure	0.000	(0.001)	w × Tenure	0.013	(0.019)
Age	0.002***	(0.001)	w × Age	0.034***	(0.012)
Hometown	−0.015***	(0.005)	w × Hometown	−0.329***	(0.092)
Observations	5,680		R^2	0.040	

Note: standard error is in parentheses. P values are for a two-sided test based on normal distribution. ***$P<0.01$, **$P<0.05$, *$P<0.1$.

intensity. Table E4 in Supplementary Information lists the estimated coefficients of the two-regime SDM for the four matrices.

Mayors' characteristics on carbon emission

The effects of mayors' characteristics on carbon intensity were also estimated. Table 2 shows that the mayor's education degree is associated with reducing the city's carbon intensity. This suggests that mayors with higher education levels may be more concerned about local carbon regulations, which is consistent with previous studies[25,26]. Mayors in science-related majors can reduce carbon intensity by 1.5% compared with social science-related majors. This suggests that mayors with science-related backgrounds are more likely to acquire and improve their knowledge and skills regarding carbon regulations. With regard to the age of the mayor, we found that carbon intensity increases by 0.2% annually due to officials' aging. One explanation for this relationship could be the absence of promotional incentives for older mayors[27]. In addition, officials who work in their birthplaces exhibit a 1.5% decrease in carbon intensity compared with those outside their hometowns. Previous research has shown that mayors who work in their hometowns are familiar with local conditions, enabling them to implement tailored measures to promote low-carbon development[28]. Table 2 also shows that the major and hometown of neighboring mayors have negative associations with local carbon intensity, while the age coefficient is positive. This suggests that the personal characteristics of neighbors may play a significant role in strategic interactions. We also control other socioeconomic variables. For more details, see Part E.5 in Supplementary Information.

Discussion

Cities have become the dominant hub of global carbon emissions. Therefore, the efforts and measures taken by cities are critical in combating climate change. Previous studies have identified and examined the factors influencing cities' carbon emissions. However, few studies have explored the effect of horizontal interactions among local governments. Thus, we supplemented the existing literature and extended our research to include the strategic interaction of local governments and the role of mayors to gain insights into the progress of cities' efforts to control carbon intensity. We aim to offer a fresh perspective on achieving carbon peak and neutrality.

The study found that the strategic interaction between geographically, economically and administratively related cities significantly reduced local cities' carbon intensity. A 1% decrease in the carbon intensity of neighboring cities resulted in a 0.792% decrease in the carbon intensity of local cities. The results were tested for robustness by replacing the dependent variables and the estimation methods. Our heterogeneity analysis revealed that the strategic interaction effect between cities peaked at 400 km and disappeared at 1,400 km. The interaction effect showed an upward trend, particularly after the 12th FYP, and was more pronounced in nonpilot cities, cities that ranked in the bottom 50%, and in the cadre turnover years. Moreover, the carbon regulations of cities exhibited a strategic interaction pattern of 'imitative competition'. In other words, local cities would follow suit if neighboring cities strengthened or weakened their carbon regulations. We also reveal that mayors play a crucial role in combating climate change, and those who are younger, have science-related backgrounds, have higher levels of education and work in their hometowns are significantly associated with greater reductions in carbon intensity.

These findings have important policy implications for future research. It is crucial to incorporate binding carbon performance and related elements, such as declining carbon emissions per unit of GDP and declining energy consumption per unit of GDP, to reduce distortions in local officials' behavior, such as imitating the laggards. When evaluating officials, it is also important to consider the public's perception of carbon performance. To improve government accountability, the National People's Congress and Chinese People's Political Consultative Conference should be utilized for supervision. Differential elections can also be organized to align officials' career paths with the public's desire for green development.

Second, as the strategic interaction effect is more pronounced within provincial boundaries (within 400 km), provincial governments should pay particular attention to the interactive effect when designing carbon plans. Additionally, nonpilot cities, cities in the bottom 50%, and cities with the cadre turnover are more vulnerable to the influence of their neighbors. Therefore, it is beneficial to encourage positive carbon-based interaction by following the example of successful leaders and frontrunners is imperative to sharing practical experiences with surrounding cities. This also suggests the necessity of a 'joint prevention and control' approach to carbon governance, characterized by trans-regional cooperation and learning between local governments. Higher levels of government should guide local governments in adapting 'imitate competition' to suit local conditions.

Third, strengthening the administrative capacity of mayors. Establishing a carbon-related capacity training system for officials without carbon governance backgrounds would be beneficial. State-led carbon reduction initiatives can also select agents on the basis of the mayors' characteristics, such as young, native and highly educated officials.

This study has limitations that can be improved in future research. The lack of relevant official data makes obtaining more information about mayors' behavior challenging. It would be worthwhile to study the mechanism of local governments' strategic interaction in carbon governance and examine the attitudes of local leaders toward the interaction between carbon regulations and their enforcement. In addition, the estimated coefficients in this study cover only the average interaction effect on carbon regulations from 2000 to 2019 due to the deficiency of generating dynamic matrices in the SDM model. Ideally, a spatial panel weight matrix should be constructed annually for cities with changing neighborhoods.

Methods

Econometric model

The theoretical analysis reveals that the carbon emissions of city i can be written as $\text{Carbon}_i = f(\text{Carbon}_j, X_i)$. This implies that a city's carbon emission is influenced by its control variables and neighboring cities' carbon emissions. However, the classical linear model implies that individuals are independent, which results in biased coefficient estimators for spatial data. Thus, to estimate the strategic interaction, spatial econometrics is required. The SDM, proposed by LeSage and Pace[29], can simultaneously incorporate the spatially lagged dependent variable, spatially lagged independent variables, and a spatially autocorrelated error term. It theoretically confirms the interaction effects related to peers and solves methodological endogeneity and geographic autocorrelation problems of the spatial autoregressive model (SAR) and spatial error model (SEM). Therefore, it should be prioritized in empirical analysis. The model is shown in equation (1):

$$\ln\text{CI}_{it} = \rho \sum_{j\neq i}^{n} W_{ij} \ln\text{CI}_{jt} + \beta_1 X_{it} + \beta_2 \sum_{j\neq i}^{n} W_{ij} X_{jt} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where $\ln CI_{it}$ denotes the carbon intensity level of city i in year t. Like time lags, $\sum^{n}_{j\neq i} W_{ij}\ln CI_{jt}$ is the spatial lag term, and W_{ij} is the spatial weights matrix, defining the distance between city i and city j. Geospatially, economically and administratively related neighbors between cities are considered. Table D2 in Supplementary Information presents the spatial weight matrices. Parameter ρ measures the effect of the strategic interaction on carbon regulations. X_{it} denotes the city-level control variables, including the personal characteristics of mayors and socioeconomic factors, and $\sum^{n}_{j\neq i} W_{ij}X_{jt}$ denote the spatial lag term of X_{it}. μ_i is the city fixed effect, reflecting cities' socioeconomic differences, λ_t represents each period's macro shocks and policy effects, and ε_{it} is the random error term.

There is a spatial lag term in equation (1), indicating that the estimation coefficients do not reflect the marginal effect of the independent variables on the dependent variables[29,30]. A spatial econometric model can explain the direct and indirect effects. To further assess these effects, we revised equation (1) as equation (2):

$$\begin{aligned}\ln CI_{it} = {} & \left(I-\rho\sum^{n}_{j\neq i}W_{ij}\right)^{-1}\left(X_{it}\beta_1+\sum^{n}_{j\neq i}W_{ij}X_{jt}\beta_2\right)+\left(I-\rho\sum^{n}_{j\neq i}W_{ij}\right)^{-1}\mu_i \\ & +\left(I-\rho\sum^{n}_{j\neq i}W_{ij}\right)^{-1}\lambda_t+\left(I-\rho\sum^{n}_{j\neq i}W_{ij}\right)^{-1}\varepsilon_{it}\end{aligned} \tag{2}$$

Equation (1) estimates the effect of the interaction and assumes that the impact of other cities on city i is the same. However, the dynamic responses of cities may differ because of their different carbon emission levels. To identify the cities' different responses, we used the two-regime SDM proposed by Fredriksson and Millimet[31] and Konisky[32] to test for an asymmetrical strategic interaction, as follows:

$$\begin{aligned}\ln CI_{it} = {} & \delta_1 d_{it}^{k(k=1,2)}\sum_{j=1}^{N}W_{ij}\ln CI_{jt}+\delta_2\left(1-d_{it}^{k(k=1,2)}\right)\sum_{j=1}^{N}W_{ij}\ln CI_{jt}+\beta X_{it} \\ & +\theta\sum_{j=1}^{N}W_{ij}X_{it}+\alpha+\mu_i+\lambda_t+\varepsilon_{it} \\ d_{it^1} = {} & \begin{cases}1, \text{ if } \ln CI_{i,t} > \sum_{j=1}^{N}W_{i,j}\ln CI_{j,t},\ i\neq j \\ 0, \text{ others}\end{cases} \\ d_{it}^2 = {} & \begin{cases}1, \text{ if } \sum_{j=1}^{N}W_{i,j}\ln CI_{j,t} < \sum_{j=1}^{N}W_{i,j}\ln CI_{j,t-1}, i\neq j \\ 0, \text{ others}\end{cases}.\end{aligned} \tag{3}$$

Generally, dynamic interaction behavior can be empirically analyzed in two ways. The first is to examine how neighbors' spatial differences in carbon intensity affect those of local cities (condition d_1). The second is to examine how neighbors' temporal changes regarding carbon intensity affect that of local cities (condition d_2). In equation (3), d_{it} is a binary indicator variable that depicts the asymmetric strategy behavior of the two situations regarding their carbon intensity. In condition d_1, d_{it}^1 is equal to 1 if city i has a higher carbon intensity level than their neighboring cities' weighted average; otherwise, it takes the value of 0. Coefficient δ_1 is the response coefficient of carbon regulations in city i when the neighboring cities' average carbon intensity levels are lower than those of city i. Conversely, δ_2 reports the coefficient when the neighboring cities' carbon intensity level are equal to or higher than those of city i. In condition d_2, d_{it}^2 is equal to 1 if the carbon intensity levels of neighboring cities in year t are lower than those in year $t-1$; otherwise, it takes the value of 0. The coefficient δ_1 is the response coefficient of the carbon intensity level in city i when the neighboring cities decrease their carbon intensity compared with the previous year. Conversely, δ_2 reports the coefficient when the neighboring cities do not change or increase their carbon intensity levels compared with the previous year. The other terms are identical to those in equation (1).

Table E3 in Supplementary Information presents the five strategic interaction patterns based on the value and significance levels of δ_1 and δ_2. Form 1 is the 'imitative competition' pattern. In this form, $\delta_1 > 0$ and $\delta_2 > 0$, which denote whether neighboring cities have higher or lower carbon intensity levels than city i or their previous year, once they increase or reduce their carbon intensity, city i will follow suit. 'Imitative competition' involves both the 'race to the top' and 'race to the bottom' patterns, which is consistent with hypothesis 2 in Part A.2 in Supplementary Information. Form 2 is the 'race to the top' pattern. In this form, $\delta_1 > 0$, while $\delta_2 < 0$ or δ_2 are insignificant, meaning that, when neighboring cities have lower carbon intensity levels than city i or their previous year, city i will follow suit. Conversely, form 3 is the 'race to the bottom' pattern. In this form, $\delta_2 > 0$, while $\delta_1 < 0$ or δ_1 are insignificant, indicating that, when neighboring cities have higher carbon intensity levels, city i will follow suit. Form 4 is the 'differentiated interaction' pattern. In this form, $\delta_1 < 0$, $\delta_2 < 0$; $\delta_1 < 0$, while δ_2 is not significant; $\delta_2 < 0$, while δ_1 is not significant. Take $\delta_1 < 0$ while $\delta_2 < 0$ as an example. Neighboring cities have lower carbon intensity levels than city i or the previous year, and once they decrease carbon intensity, city i will inversely increase carbon intensity, which validates the classic free-riding phenomenon. Form 5 signifies 'no strategy', with both δ_1 and δ_2 being nonsignificant.

Variables and data

For dependent variable, this study uses carbon intensity because it is highly correlated with government behavior. The national 12th FYP has raised the reduction of carbon dioxide emissions per unit of GDP to the key objective of carbon reduction[33]. The binding goals accompanied by the Chinese-style Performance Appraisal System motivated mayors to put more effort into reducing carbon intensity. We take its logarithmic form. The carbon emission data come from Carbon Emissions Accounts and Datasets (CEADs, https://www.ceads.net.cn/). The emission inventories are compiled for 47 economic sectors and include energy-related emissions for 17 types of fossil fuels and process-related emissions from cement production[34].

This study included two categories of control variables. One related to city officials' characteristics. Education level is used to measure officials' ability[35], and carbon intensity may be negatively correlated with officials' ability[36]. Age denoted the age of the local officials of city i in year t, as older leaders are less likely to reduce carbon intensity actively[35]. In this study, we considered the mayors' major as a factor that could influence a city's carbon reduction efforts. According to the Ministry of Education's discipline classification, science-related majors include science, technology, engineering, mathematics and so on, while social science majors include economics, geography, history, law, philosophy, political science, anthropology, archeology and so on. Mayors with science-related backgrounds may have a relative advantage in carbon emissions accounting and technology or in designing emission reduction plans, leading to a potential reduction in carbon intensity[37]. We included the mayor's tenure because some studies have suggested that career-oriented officials are more likely to reduce carbon emissions during their first few years[38]. Finally, we measured whether an official had served in their hometown, as local knowledge enables carbon reduction policies to be tailored for local development[39].

The second variable category included socioeconomic characteristics. We used gross domestic product per capita (PGDP) to measure a city's economic development level. According to the environmental Kuznets curve hypothesis, a U-shaped relationship exists between economic growth and environmental quality[40]. Therefore, we incorporated PGDP and its quadratic term into the empirical analysis using its logarithmic form. We used fiscal decentralization (FD) to reflect local governments' financial autonomy. A higher degree of FD implies more authority for mayors to implement environmental regulations.

We calculated it as follows: fdc/(fdn + fdp + fdc), where fdn, fdp and fdc represent budgetary expenditure per capita at the national, provincial and city levels, respectively. We determined the Open variable by the total import and export trade volume ratios to GDP. We considered the pollution haven and halo hypotheses in this context[41]. The pollution haven hypothesis posits that pollution-intensive companies seek investment possibilities in nations with lax environmental standards[42], while the pollution halo hypothesis argues that foreign firms that meet higher environmental standards can improve the ecological quality of their host country[43]. As trade has opposing effects on the carbon intensity of a host area, its impact on carbon intensity is ambiguous. We used technological innovation, represented by the number of green patents, as this aspect facilitates the development of energy-saving and emission-reducing technologies, thereby reducing carbon intensity[44]. We used the logarithmic form of technological innovation in the analysis. As our primary focus was on carbon intensity, we used the ratio of secondary industry value added to GDP to illustrate a city's industrial structure[45]. We used fixed-asset investment (fixed) as it plays a significant role in carbon intensity; increasing investment in industry is the mayors' principal strategy for promoting local economic development and increasing carbon intensity[46]. We used its logarithmic form. Finally, we used the urbanization rate to measure the proportion of the urban population to the total population, as a high urbanization rate is associated with rapid economic development and high carbon intensity.

Our panel data included 284 cities from 2000 to 2019. We carefully screened the data to eliminate samples with missing information. We obtained the socioeconomic data from the China Statistical Yearbooks, China Science and Technology Statistical Yearbooks, China City Statistical Yearbooks and the CEIC database. Carbon emission data comes from the CEADs database. To acquire the mayors' personal characteristics data, three main steps are followed. First, we manually collected the names of successive mayors of the Chinese cities from 2000 to 2019. Second, based on the information of the mayors' name and year in office, we manually extracted the individual information of the mayors from Local Party and Government Leaders Personality Database in China Economic Network[47], the official websites of city governments and the Baidu Wikipedia database. The information includes gender, birthdate, birthplace, education level, profession and so on. Third, we quantified these raw data. The monetary variables have all been deflated to 2000 constant prices. For the descriptive statistics of the data, see Table F1 in Supplementary Information.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Most of the data in this study are sourced from publicly available data sources. Datasets that are allowed to be shared are available through GitHub at https://github.com/2020000927/-Dynamical-Systems-Laboratory-Strategic-interaction-.git (ref. 48).

Code availability

Analysis was performed using custom-made scripts coded in Stata (Version 16) and MATLAB (Version R2023a). The do file includes the code of baseline model, robust test and temporal and spatial heterogeneity analysis. The m file includes the code of strategic interaction pattern, heterogeneity analysis pilot, rank and turnover). Scripts used for this study are available through GitHub at https://github.com/2020000927/-Dynamical-Systems-Laboratory-Strategic-interaction-.git (ref. 48).

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Author contributions
B.Z.: formal analysis, methodology, data curation, writing—original draft, and visualization. C.W.: conceptualization, writing—review and editing, and project administration.

Competing interests
The authors declare no competing interests.

Additional information
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n/a	Confirmed	
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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	No software was used to collect data.
Data analysis	The primary data is developed by Stata (Version 16) and Matlab (Version R2023a).

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

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Scripts and datasets that are allowed to be shared are available at https://github.com/2020000927/-Dynamical-Systems-Laboratory-Strategic-interaction-.git.

Human research participants

Policy information about studies involving human research participants and Sex and Gender in Research.

Reporting on sex and gender	In this study, we did't consider sex and gender, because they are not important for carbon regulation.
Population characteristics	This study describes the age, education level, major, tenure, turnover and hometown of mayors.
Recruitment	This study considers 284 cities of China, the missing data is mainly due to incomplete statistics and no systematic error.
Ethics oversight	Authors of Renmin University of China all approve the study protocol.

Note that full information on the approval of the study protocol must also be provided in the manuscript.

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All studies must disclose on these points even when the disclosure is negative.

Study description	This study offers a fresh perspective of horizontal strategic interaction of local governments to explain cities' carbon reduction.
Research sample	China's 284 cities from 2000 to 2019.
Sampling strategy	The sample involved in this study is 284 cities, accounting for 97% of the total samples. The missing data is due to the lack of statistical indicators.
Data collection	Socioeconomic data come from official statistical yearbooks. Carbon emissions come from the CEADS database. The data of mayors' characteristics is manual collection by authors from Local Party and Government Leaders Personality Database in China Economic Network(http://district.ce.cn/zt/rwk/index_21094.shtml), the official websites of city governments and the Baidu Wikipedia database.
Timing	Our panel data included 284 cities from 2000-2019.
Data exclusions	Due to unavailable data.
Non-participation	No participant was included in this study.
Randomization	The study relies on observational data, hence randomization was not an option.

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Methods

n/a	Involved in the study	
☒	☐	ChIP-seq
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☒	☐	MRI-based neuroimaging