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Does carbon emissions trading facilitate carbon unlocking? Empirical evidence from China

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ABSTRACT

Carbon emissions trading is essential for reducing carbon emissions, and its role in regional carbon unlocking needs further clarification. This study uses the difference-in-differences (DID) model and synthetic control model (SCM) to evaluate the carbon unlocking effect of China's six pilot carbon trading provinces. This study found that (1) carbon lock-in effects in China are mainly influenced by technology lock-in and fixed input lock-in; (2) each province's overall carbon lock-in level presents a decreasing trend yearly, and the regional distribution presents characteristics of "low in the east and high in the west"; (3) carbon emissions trading pilot policies effectively promote the carbon unlocking effect in pilot regions overall, with Guangdong having the most significant unlocking effect. Conversely, Beijing, Hubei, Chongqing, and Shanghai also had different degrees of carbon unlocking. Finally, (4) an assessment of impact mechanisms indicates that technology and institutions have a significant mediating role in effectively promoting carbon unlocking under the carbon trading policy. Conversely, social behavior has an inverse effect, and fixed assets are not affected by the policy. This study demonstrates the carbon unlocking effect of carbon emissions trading and provides a quantitative reference for implementing carbon emissions trading policies and determining carbon unlocking paths.

KEYWORDS

Carbon lock-in; Indicator system; Carbon emissions trading; DID; SCM

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1. Introduction

According to the International Energy Agency (IEA), China's total CO2 emissions reached 54.07 tons in 2005 (IEA, 2021b), surpassing those of the United States as the world's top carbon emitter. By 2021, China's CO2 emissions have exceeded 11.9 billion tons, accounting for 33% of the total global CO2 emissions (IEA, 2021a). Carbon emissions can be reduced by strengthening environmental policies (Qin et al., 2021). Consequently, the Chinese government has adopted a series of complex, flexible, authoritative, and low-cost policy instruments to reduce carbon emissions from conventional energy systems (Li and Taeihagh, 2020). In 2013, China launched pilot carbon emissions trading policies in Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen[1]. These policies first began with the power sector, which have the highest cost of emissions reduction (Lin and Jia, 2017) and incorporated different sectors according to each pilot project's economic structure and other characteristics, making exploratory attempts to reduce carbon emissions and achieve remarkable results. Since December 31, 2021, more than 2,900 emitting enterprises and units were included in the seven pilot carbon markets. Moreover, a total of approximately 8 billion tons of carbon emission allowances (CEA) were allocated. This resulted in a cumulative turnover of 483 million tons of CEA, and a turnover of RMB 8.622 billion. The cumulative volume of the CEA traded in the market reached 179 million tons, with a turnover of RMB 7.684 billion.

The reason for the rapid growth of China's carbon emissions is overreliance on the carbon-intensive fossil fuel-based energy system over decades of reform and opening up and the rebound effect of China's energy economy. This eventually evolved into a "carbon lock-in" based on a "technology-institutional complex" (Karlsson, 2012). Carbon lock-in refers to the long-term persistence of fossil fuel-based infrastructure or systems over time. This prevents a shift to more efficient and energy-saving technologies or non-fossil fuel energy sources, including renewable energy (Unruh, 2000). Hence, carbon lock-in often limits low-carbon technological, economic, political, and social efforts at the source, which will ensure that China's total carbon emissions continue to increase. The carbon trading market is considered a combined policy to reduce CO2 emissions and mitigate climate warming. Currently, more than 20 carbon markets operate globally and can be tailored according to each country's development level (Kiss and Popovics, 2021). The relationship between carbon trading and carbon lock-in is mainly reflected in the following. First, carbon trading allows high-carbon emitting companies to purchase carbon allowances from low-carbon emitting companies, thereby reducing carbon emissions. Owing to the considerable task of reducing carbon emissions and the time crunch, carbon allowances are expected to gradually tighten. Thus, an increase in carbon trading prices is inevitable. This will increase cost pressure on enterprises with high carbon lock-in, high reliance on carbon-based energy systems, backward technology, and a shortage of allowances. However, it will bring significant benefits to enterprises that have already achieved carbon unlocking, advanced technology, and a surplus of allowances. Second, carbon trading is an institutional tool that utilizes policies and market-based means to promote and lead high-carbon emission enterprises to realize the conversion of old and new kinetic energy for enterprise development at low cost. These force enterprises to replace their outdated production capacities, realize low-carbon transformation, and upgrade to achieve carbon unlocking. ETS can facilitate the transition from large-scale coal-fired power generation technologies to low-carbon power generation technologies (Rogge and Hoffmann, 2010).

Carbon emissions trading policies can theoretically affect carbon lock-in to a certain extent; however, whether this effect exists and its specific degree of impact remain unknown. Hence, this study will use China's provinces as its research object to conduct the following explorations: (1) quantitatively measure the extent of carbon lock-in in Chinese provinces; (2) explore the effect of China's carbon emissions trading pilot policies on Chinese carbon unlocking; and (3) assess the heterogeneity of carbon unlocking across pilot regions, which is helpful for

[1] Carbon emissions trading market in China is briefly introduced in Appendix A.

understanding the effect of ETS in different regions.

Our study contributes to the literature in two ways. First, we improved the indicator system for measuring carbon lock-in by incorporating enterprise nationalization and urbanization levels into the system. We extend the applicability of the projection tracing model to panel data. Second, we link carbon emissions trading policies with degree of carbon lock-in and use policy effect evaluation models to evaluate the effect of carbon emissions trading on carbon lock-in. Finally, we explore both overall effects and differences in the effects of different pilots.

The remainder of this paper is structured as follows. In Section 2, we review related literature on carbon unlocking. This is followed by a description of the research method in Section 3. Section 4 presents empirical results, and Section 5 discusses the empirical results. Finally, Section 6 concludes the study.

2. Literature review

"Carbon lock-in" was first proposed by the Spanish scholar Unruh in 2000 (Unruh, 2000). The concept is based on the coevolution of carbon-based energy technologies and institutional systems, driven by increasing returns to scale, strengthening the system through continuous feedback, and resulting in a "technology-institution complex" (TIC). Over time, technological or institutional changes are unlikely to occur without external drivers as the energy system develops path dependencies to produce equilibrium.

The causes of carbon lock-ins are similar in countries worldwide. Some scholars (Janipour et al., 2020; Seto et al., 2016; Susskind et al., 2020; Xihua et al., 2013) have concluded that the mechanism of carbon lock-in is a combination of infrastructure, technology, institutions, and social behavior. Specific strategies for unlocking carbon have also been suggested. More than 50 barriers to technology deployment in the carbon unlocking process were identified and described, which could be addressed more effectively through policy (Brown et al., 2008).

Some scholars have explored the state of carbon lock-in at the industrial and sectoral levels, and some have analyzed the causes of carbon lock-in in the Spanish wind and solar industries (McKie and Galloway, 2007). Carley (2011) explored the driving factors of carbon lock-in reduction in the US electricity sector. Driscoll (2014) examined carbon locking in the transport sector of two similar cities in Denmark and in the US. Wang et al. (2020) studied the characteristics and influencing factors of carbon lock-in in China's manufacturing sector. Bauer et al. (2022) examined carbon lock-in at each stage of the entire plastic value chain and suggested means of mitigation . From this perspective, scholars have primarily focused on high carbon-emitting industries to target carbon lock-in research. Hence, our study assesses the causes, evolutionary characteristics, and influencing factors of carbon lock-in in each sector as the main research content of industry carbon lock-in.

Some Chinese scholars have conducted regional studies on carbon lock-in at provincial and municipal levels in China (Long et al., 2016; Xu et al., 2022; Yingzhi and Yan, 2018). Using spatial econometric models such as the Moran index, they found that the spatial distribution of carbon-locking effects in China is significantly unbalanced. This presents pattern of low in the east and high in the west, aggregation characteristics, and a significant spatial spillover effect.

The quantitative analysis of carbon lock-in can be broadly divided into two categories of existing research. The first measures the level of carbon lock-in quantitatively. The primary methods include carbon overload rate (Xu et al., 2022), input–output (Jin and Yingzhi, 2015), construction of indicator systems (Niu and Liu, 2021), and data envelopment analysis (DEA) models (Zhu, 2018). The second explores the factors influencing carbon locking using the partial least squares (PLS) path modeling method (Jin and Yingzhi, 2015); stochastic impacts by regression on population, affluence, and technology (STIRPAT) model (Wang et al., 2013); and the geographically and temporally weighted regression (GTWR) model (Wang et al., 2020).

Simultaneously, some scholars have evaluated the effectiveness of China's carbon emissions trading policy. The main methods include the difference-in-differences (DID) model (Xuan et al., 2020; Zhang and Zhang, 2020), propensity score matching differences-in-differences (PSM-DID) model (Pan et al., 2022; Wang et al., 2022a), synthetic control method (SCM) (Wang et al., 2022b), and computable general equilibrium (CGE) model (Zhang et al., 2020; Zhang et al., 2017).

These studies found that carbon emissions trading can significantly reduce carbon emissions of pilot cities and has sustainable effect. This study also found that carbon emissions trading in China contains far-reaching implications for the economy, energy, and environment. Carbon emissions trading is helpful for reducing carbon emission costs and decreasing energy consumption and carbon emissions. This may have different effects on different provinces.

Research on carbon lock-in and credits has made significant progress. However, deficiencies remain in the following aspects. (1) The indicators used for measuring carbon lock-in are not sufficiently comprehensive. Most methods for measuring carbon lock-in use carbon emissions and sinks as leading indicators. Other indicators affecting degree of carbon lock-in are often ignored, which may lead to carbon lock-in measurement values that cannot fully reflect the degree of carbon lock-in. (2) The effects of carbon emissions trading policies on carbon unlocking has not received much attention. Most studies have focused on the ultimate effects of policies on CO2 emissions. Limiting the effect of the policy on end-of-pipe treatment may hinder tackling carbon emissions as the root cause, resulting in the long-term effect of the policy, which may not be obvious. (3) The heterogeneous effects of different carbon emissions trading pilots have not been adequately studied.

Hence, based on annual panel data from 30 provinces in China from 2007 to 2019, this study first constructs a carbon lock-in measurement index system. Moreover, it calculates carbon lock-in effect values of 30 provinces over 13 years using the projection pursuit evaluation model based on the real-coded accelerating genetic algorithm (RAGA-PP model). Then, the effects of the carbon emissions trading policy on the overall and individual carbon lock-in levels in the pilot provinces were analyzed using the difference-in-differences (DID) model and the synthetic control method (SCM).

3. Research methodology and data presentation

Fig. 1 presents the research method framework of this study.

3.1. Carbon lock-in indicator system construction

Regarding existing studies (Erickson et al., 2015; Niu and Liu, 2021), this study follows comprehensiveness, validity, and independence and is based on data availability. We established the following carbon lock-in measurement and evaluation index system.

(1) Indicators for evaluating level of fixed-input carbon lock-in

Existing research suggests that long-term capital stocks (LLCS) (e.g., infrastructure and buildings) have a significant and long-lasting effect on greenhouse gas emissions. LLCS create carbon lock-in and potentially prevent rapid decarbonization of energy systems (Fisch-Romito et al., 2021). This study selects the ratio of the value-added of the secondary industry to GDP to reflect the extent to which the industrial structure of the high-carbon secondary sector deepens regional carbon lock-in. We selected three fixed asset-related indicators to reflect the use of basic equipment.

(2) Indicators for evaluating level of technology carbon lock-in

Once a particular technology becomes an enterprise’s core competitiveness, the enterprise will maintain the existing technology based on an incremental payoff mechanism, preventing the adoption and diffusion of other low-carbon technologies. This study measures the level of technology lock-in from the two aspects—the existing energy

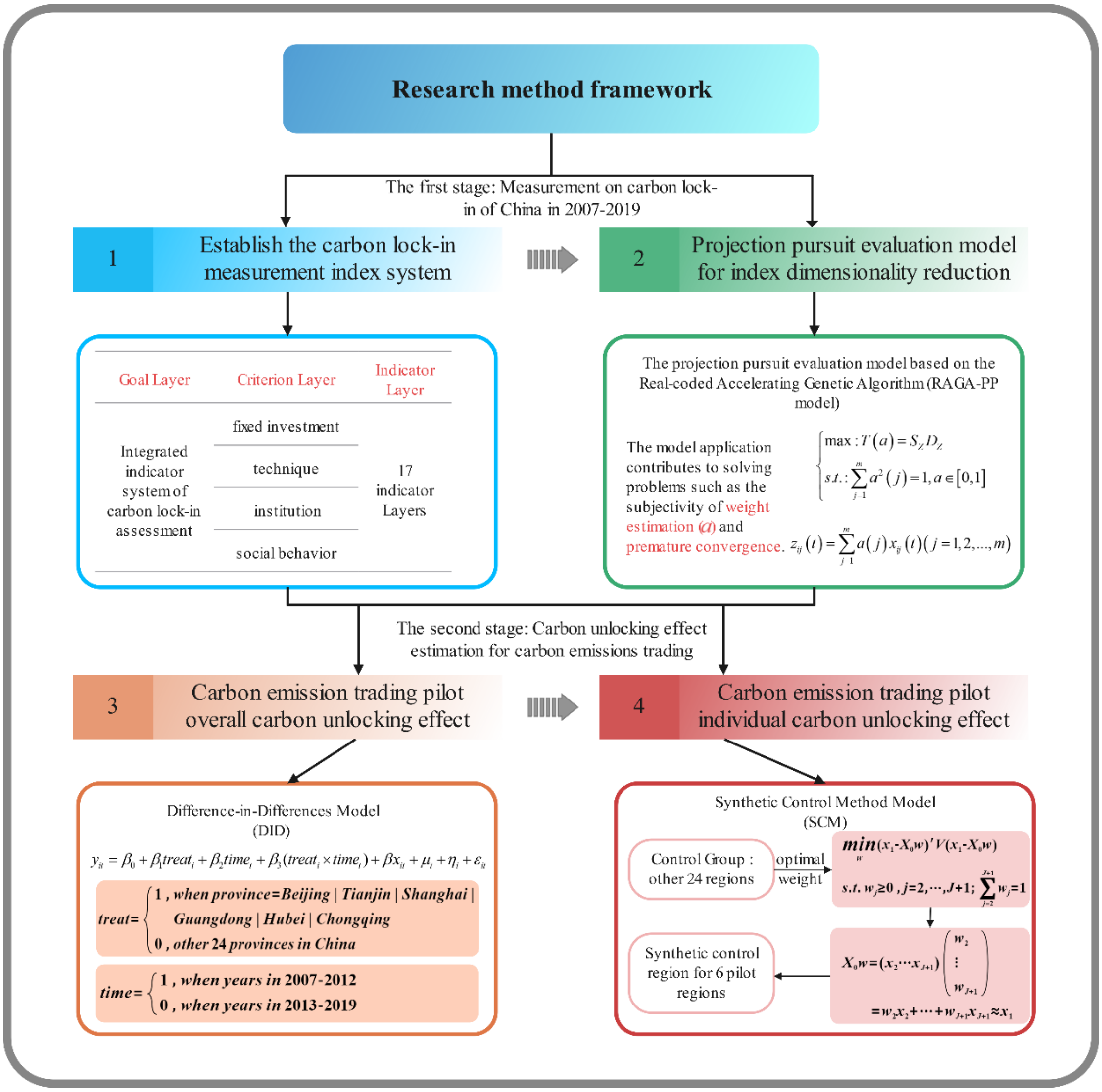


Figure 1. The process of studying how carbon emissions trading policies affect carbon lock-in methods.

technology and technological innovation and R&D.

(3) Indicators for evaluating level of system carbon lock-in

Governments can alleviate the degree of carbon lock-in through financial subsidies and low-carbon regulations. Additionally, state-controlled enterprises are directly related to state interests, which usually lead to a softening of state-owned enterprises' energy-saving and emission-reduction constraints, which is not conducive to carbon unlocking.

(4) Indicators for evaluating level of social and behavioral carbon lock-in

The behavior of individuals and societies with energy consumption or services also determines the level of carbon lock-in at a fundamental level. Urbanization determines primary energy demand for the next few decades after the completion of the region. The per capita disposable income of urban residents reflects their income level and the living standard of urban residents. The volume of passenger transportation and civilian automobile ownership are used to measure scale of development of public and personal transport in the region, and urban natural gas penetration reflects residential household energy use.

3.2. Carbon lock-in effect value assessment method—RAGA-PP model construction

This study first used the RAGA-PP model to downscale the indicator system by assigning weights to more objectively explore the carbon lock-in level of China's regional carbon emissions trading. Finally, it obtained the value of the carbon lock-in effect for 30 Chinese provinces from 2007 to 2019.

The sample is set as$x_{ij}(t)$, $i = 1, 2, \dots, n;\ j = 1, 2, \dots, m;\ t = 1, 2, \dots, T$, where $x_{ij}(t)$denotes the jth indicator for the ith province in the tth year. As different evaluation indicators have different measurement units, the original values of the evaluation indicators were standardized using the range method.

Let $a = \{ a(1), a(2), \dots, a(m) \}$ represent the projection direction vector, which can be considered the weight vector of the carbon lock-in factors. The one-dimensional projection value of the $i -$ th province in the $t -$ thyear in this direction is as follows:

$$z_{ij}(t) = \sum_{j=1}^{m} a(j) x_{ij}(t)\ (j = 1,2, \dots, m) \tag{1}$$

To optimize 1D projection values, the projection indicator function was constructed as follows:

$$T(a) = S_Z D_Z \tag{2}$$

Eq. (4), $S_Z$andD_Z refer to the standard deviation and local density of the total projection value, respectively. The specific calculation formula is as follows:

$$S_Z = \sqrt{\sum_{t=1}^{T}\sum_{i=1}^{n}\frac{(z_i(t) - \bar{z})^2}{n-1}} \tag{3}$$

$$D_Z = \sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{j=1}^{m}\left[R - r_{ij}(t)\right] \bullet o\left[R - r_{ij}(t)\right] \tag{4}$$

Eq. (5), $\bar{z}$refers to the mean of the series, $r_{ij}(t) = |\, z(i) - z(j)\, |$ refers to the intersample distance, R is the window radius of the local density, and $o(\tau) = o(R - r_{ij})$ is the unit step function, which is 1 when $R \gg r_{ij}$ and 0 if otherwise.

The search for best projection direction is transformed into a nonlinear optimal solution problem. We express the objective function and constraints as follows:

$$\begin{cases} max{:}\, T\,(a) = S_Z D_Z \\ s.t.{:} \sum_{j=1}^{m} a^2(j) = 1, a \in [0,1] \end{cases} \tag{5}$$

According to the previous step, the best projection direction is $a(j)$, which can be substituted into the function $z(i)$ to obtain the comprehensive projection value.

Traditional optimization methods do not easily solve complex nonlinear optimization problems with the projection vectors as the optimization variable. Hence, this study uses the real-coded accelerating genetic algorithm for high-dimensional global optimization.

This study had a 30×13 sample size and 17 indicators. Indicator data were standardized, and the RAGA-PP model was established by applying MATLAB programming. The parent's initial population size is selected as $n = 400$, crossover probability as $P_c = 0.8$, the mutation probability $P_m = 0.2$, number of outstanding individuals as 20, and the acceleration number as 7. As the genetic algorithm is a random search algorithm, the approximate optimal solution is obtained by random iteration; hence, the final result of each calculation will be different, but the overall trend remains the same. Therefore, this study calculates projection objective function 50 times to select the optimal result.

3.3. Evaluation method for the overall carbon unlocking level of carbon emissions trading pilot—DID model

The difference-in-differences (DID) based on "natural experiments" is widely used in policy effect assessment. Using fixed-effect estimation, we can largely avoid the endogeneity problem associated with policy as an explanatory variable. Moreover, we can control for the influence of unobservable individual heterogeneity on the explanatory variable (Angrist and Krueger, 1999). Therefore, this study uses the DID model to quantitatively assess how carbon emissions trading impact regional carbon lock-in.

This study constructs a two-way fixed effects (TWFE) model incorporating joint province-time fixed effects into the basic model. We define the proposed DID model as follows:

$$y_{it} = \beta_0 + \beta_1 treat_i + \beta_2 time_t + \beta_3 (treat_i \times time_t) + \beta x_{it} + \mu_t + \eta_i + \varepsilon_{it} \tag{6}$$

In Eq. (8), y_{it} represents the carbon lock-in effect for the ith province in the t-th year; $treat_i$ represents the experimental group dummy variable, which is 1 when the i-th province is the experimental group and 0 when the i-th province is the control group; $time_t$ represents the experimental period dummy variable, which is 1 when the carbon trading policy was implemented, and 0 if otherwise; $treat_i * time_t$ represents the joint province and time fixed effects; x_{it} refers to time-varying control variables which could impact carbon lock-in at province-level; μ_t is the time fixed effect; η_t is the area fixed effect; and ε_{it} is the disturbance term. The interaction term coefficient β_3 is the focusing coefficient and represents the impact of the national pilot carbon emissions trading policy on the carbon lock-in effect.

3.4. Individual carbon unlocking level evaluation method for carbon emissions trading pilot—SCM model

The synthetic control model (SCM) is a powerful tool for exploring the heterogeneity of carbon unlocking effects across pilots (Abadie and Gardeazabal, 2003). The synthetic control method essentially utilizes the pilot area as the treatment group, finds appropriate weight through predictor variables, weighs average value of the provinces that have not implemented the carbon emissions trading policy, and establishes the "counterfactual" control group. Thereafter, we compared the difference in carbon lock-in values between the treatment and synthetic control groups after policy implementation (i.e., policy effect).

We assume that observations are available for $N+1$ areas for T periods, with the first area (the pilot province) affected by the policy at T_0, and the other N areas as a potential control set for the first area.

$$\begin{cases} y_{it}(0), \text{Potential consequences of not implementing the policy} \\ y_{it}(1), \text{Potential consequences of implementing the policy} \end{cases} \tag{7}$$

Then, the actual observations y_{it} of $i = 1,2,\dots,N+1$ for the province for the period $t = 1,2,\dots,T$ are as follows:

$$y_{it} = y_{it}(0) + \alpha_{it} D_{it}, \text{ where } D_{it} = \begin{cases} 1, \text{ when } i = 1 \text{ and } t > T_0 \\ 0, \text{ otherwise} \end{cases} \tag{8}$$

As the "counterfactual" outcome, $y_{1t}(0)$ is not observable for the target of the intervention after the policy is implemented, synthesizing $y_{1t}(0)$ is necessary by using the pre-intervention information to select the optimal weights $W^* = (w_2^*, \dots, w_{N+1}^*)$ for control unit i. For any i, $w_i \geq 0$ and $\sum_{i=2}^{N+1} w_i = 1$, and the specific equations are synthesized as follows:

$$\hat{y}_{it}(0) = \partial_t + \theta_t X_i + \lambda_t \mu_i + \varepsilon_{it} \tag{9}$$

$$\sum_{i=2}^{N+1} w_i y_{it} = \partial_t + \theta_t \sum_{i=2}^{N+1} w_i X_i + \lambda_t \sum_{i=2}^{N+1} w_i \mu_i + \sum_{i=2}^{N+1} w_i \varepsilon_{it} \tag{10}$$

Here, X_i is the control variable, ∂_t is the time trend, λ_t is a (1 × F)-dimensional unobserved common factor, μ_i is a (F × 1)-unobserved dimensional area fixed effects error term, and ε_{it} is a temporary shock unobserved in each area with a mean value of 0. Currently, this set of optimal weights $W^* = (w_2^*, \ldots, w_{N+1}^*)$ needs to have good historical properties, satisfying the following condition:

$$\sum_{i=2}^{N+1} w_i^* y_{i1} = y_{11}, \quad \cdots, \quad \sum_{i=2}^{N+1} w_i^* y_{iT_0} = y_{1T_0} \; and \; \sum_{i=2}^{N+1} w_i^* y_i = y_1 \tag{11}$$

Abadie et al. (Abadie et al., 2010) prove that for $T_0 < t < T$, we can use $\sum_{i=2}^{N+1} w_i^* y_{it}$ as an unbiased estimate of $y_{1t}(0)$ to approximate $y_{1t}(0)$, such that the effect of estimating the policy based on the synthetic estimate is thus as follows:

$$\hat{\alpha}_{1t} = y_{1t} - \hat{y}_{1t}(0) = y_{1t} - \sum_{i=2}^{N+1} w_i^* y_{it}\, , t \in \{T_0 + 1, \ldots, T\} \tag{12}$$

3.5. Data source and processing

We obtained data from the China Statistical Yearbook, China Science and Technology Statistical Yearbook, China Fixed Assets Statistical Yearbook, China Statistical Yearbook on Environment, and CEADs Carbon Emissions Database (Guan et al., 2021; Shan et al., 2018; Shan et al., 2020; Shan et al., 2016). Sample data in this study included observation records of 30 provinces and municipalities in China from 2007 to 2019, with a sample size of 390. Tibet, Taiwan, Hong Kong, and Macao were excluded because of a lack of data for these regions. In 2018 and 2019, the proportion of depreciation of fixed assets in GDP, number of scientific research professionals in state-owned institutions, and ratio of investment in environmental pollution control to GDP was not published. This study used exponential smoothing to fill in the data.

4. Results and analysis

4.1. Measurement analysis of the regional carbon lock-in effect

Based on the RAGA-PP model, we calculated the projected intensity of 17 carbon lock-in indicators and carbon lock-in effect values of 30 Chinese provinces (municipalities) from 2007 to 2019 (Fig. 2).

First, technology and institutional lock-in have the most significant influence on China's comprehensive evaluation value of the carbon lock-in effect. Fig. 2(I) presents five indicators with a projection direction above 0.3, in descending order—urban natural gas penetration (D4), state-controlled enterprises level (C4), transaction value in the technical market (B4), carbon emission intensity of fixed assets (A3), and internal expenditure of R&D (B3)—which have a large contribution rate in the measurement of the carbon lock-in effect and are the main factors influencing level of carbon locking. Within the social behavior domain, only the indicator of urban natural gas penetration significantly contributes to level of carbon lock-in, while the rest contribute only weakly. However, residential household energy use is already at its limit and unlocking carbon from residential household energy use is difficult. Therefore, to achieve carbon unlocking, technological innovation is necessary, with state-owned enterprises takeleading carbon unlocking.

Second, the degree of carbon lock-in in China's provinces presents an overall decreasing yearly trend . Fig. 2(II) shows that the value of the carbon lock-in effect in 30 provinces (municipalities) decreased by 0.433 in 2007–2019, and 12 provinces (municipalities) had a reduction of 0.5 or more in the carbon lock-in effect value. Among them, Guangdong Province had the best carbon unlocking impact, with a decrease of 0.876, and Liaoning Province had the least significant carbon unlocking effect, with a 0.138 reduction. The degree of carbon lock-in in most provinces presented a slight upward trend in 2011–2012 and 2017–2018, but declined in the following years. Overall, China's carbon lock-in has presented an overall decreasing trend over 13 years, from 2007 to 2019, which indicates a good result for the sustainable development of low-carbon energy.

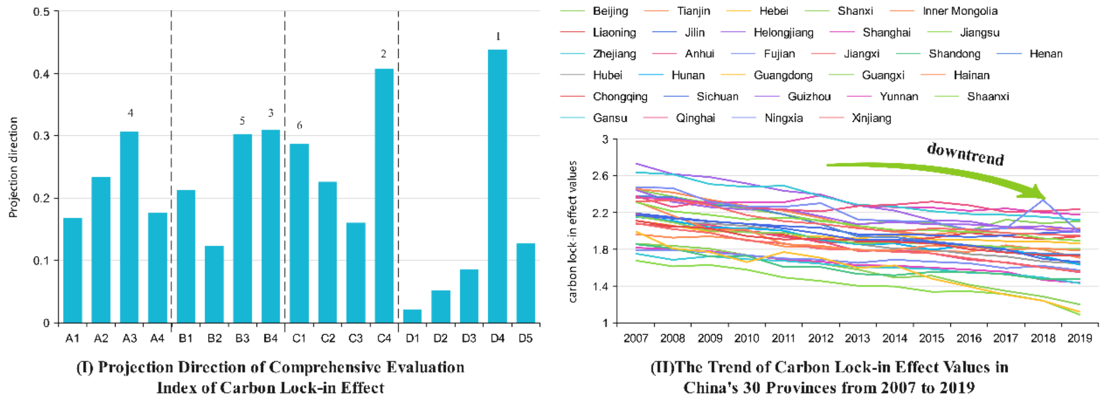
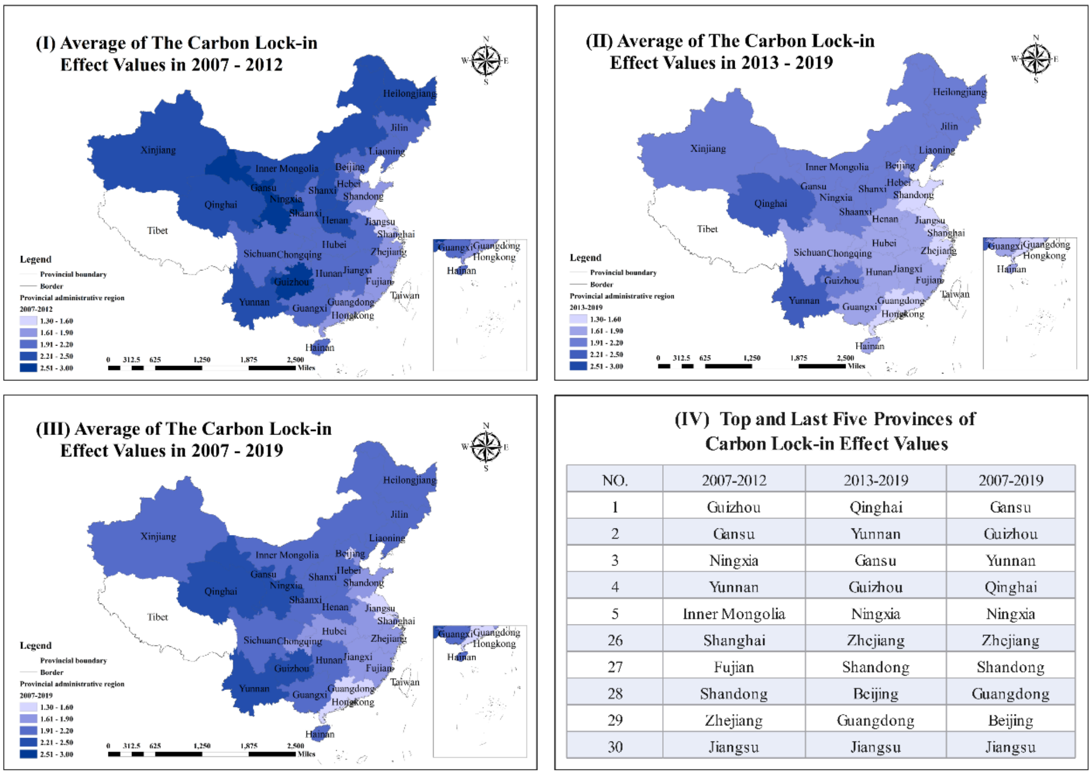


Figure 2. Projection direction of comprehensive evaluation index of carbon lock-in effect and trend of carbon lock-in efficiency values in China.



NO.	2007-2012	2013-2019	2007-2019
1	Guizhou	Qinghai	Gansu
2	Gansu	Yunnan	Guizhou
3	Ningxia	Gansu	Yunnan
4	Yunnan	Guizhou	Qinghai
5	Inner Mongolia	Ningxia	Ningxia
26	Shanghai	Zhejiang	Zhejiang
27	Fujian	Shandong	Shandong
28	Shandong	Beijing	Guangdong
29	Zhejiang	Guangdong	Beijing
30	Jiangsu	Jiangsu	Jiangsu

Figure 3. Development of carbon lock-in in each province (municipalities) in China.

Fig. 3 presents the distribution and ranking of the average carbon lock-in of China's 30 provinces (municipalities) before and after implementing carbon emissions trading in 2013. Fig. 3 shows that the geographical distribution of the carbon lock-in effect is characterized by "low in the east and high in the west." Fig. 3(I) indicates that, from 2007 to 2012, only Guizhou and Gansu had an average projection of the carbon lock-in effect of over 2.5, while Guizhou reached 2.548. The average predicted value of carbon lock-in in eight provinces was between 2.2 and 2.5, mostly in the western region. The lowest value for the carbon lock-in effect is 1.574 in Jiangsu. The mean projection of the carbon lock-in effect was 1.6 to 1.9 in seven provinces, mainly in the eastern region. Fig. 3(II) indicates that, from 2013 to 2019, Qinghai had the highest projected mean value of carbon lock-in effect at 2.259. Conversely, Jiangsu had the lowest projected mean value of carbon lock-in effect at 1.302. Although degree of carbon lock-in decreased and changed slightly in ranking for all provinces, the western region still had the highest level of carbon lock-in.

The six pilot regions for carbon credits saw a slight change in the ranking of each province in projection average of the carbon lock-in effect, before and after implementing carbon trading credits in 2013. Specifically, Beijing dropped three places, Shanghai dropped one place, Guangdong dropped five areas, and Hubei dropped seven places; conversely, Tianjin and Chongqing moved up three and four places, respectively. Whether carbon trading policy influences these ranking changes needs further examination. This study uses the DID and SCM models for specific analyses.

4.2. Overall analysis of the carbon unlocking effect of carbon emissions trading

In this study, the first batch of China's carbon emissions trading pilot policy is considered as a "quasi-natural experiment," with six provinces—Beijing, Tianjin, Shanghai, Chongqing, Hubei, and Guangdong—as the experimental group. Moreover, Shenzhen is included in the Guangdong experimental group as it is part of Guangdong province. The remaining non-pilot provinces served as the control group.

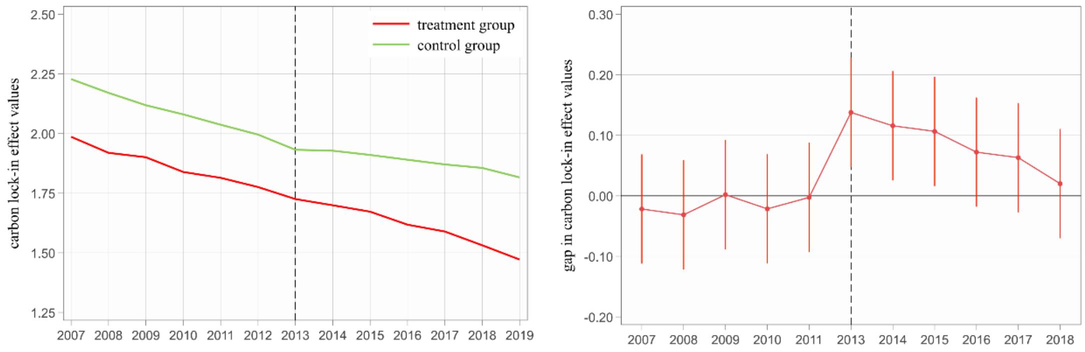
In October 2011, the National Development and Reform Commission (NDRC) issued a notice on the launch of pilot carbon emissions trading. Moreover, it marks the official launch of China's pilot carbon emissions trading markets, with seven operating in the second half of 2013. Therefore, year 2013 is established as the time point (i.e., 2007–2012) is when the policy is not implemented, and 2013–2019 is when the policy is implemented. The overall carbon unlocking effect of policy implementation is analyzed below using the DID method.

This study selected the following control variables by referring to the existing literature (Liwen et al., 2020). (1) Foreign direct investment (FDI), expressed by FDI as a share of GDP, and the choice of technology for bilateral financing significantly impact on global decarbonization and future climate change (Chen et al., 2021). Therefore, FDI, which represents bilateral financing, was used as a control variable. (2) Regional construction level (RCL) was expressed as cement production. Owing to the large amount of cement used in regional construction, the decomposition of calcium carbonate during cement production generates CO2, which increases degree of carbon lock-in.

4.2.1. Parallel trend hypothesis testing

While DID can largely avoid the problem of reverse causality and endogeneity of policy effects, its use has substantial qualification in that the treatment and control groups have an identical trend before the satisfaction event. We first tested the hypothesis of parallel trends in the carbon lock-in coefficients of the treatment and control groups.

Fig. 4(I) results indicate that the trend of the carbon lock-in degree for the treatment and control groups from 2007 to 2013 is basically the same. Conversely, from 2013 to 2019, the carbon lock-in degree for provinces implementing carbon emissions trading was significantly lower than that for provinces not implementing carbon emissions trading. Fig. 4(II) presents the results of the gap in the carbon lock-in effect values of the treatment and



(I) Parallel Trend Test of Carbon Lock-in Effect Value in Treatment Group and Control Group

(II) The Gap in Carbon Lock-in Effect Value of Treatment Group and Control Group

Figure 4. Parallel trend test for carbon sequestration in treatment and control groups.

control groups based on the event analysis method. Before the pilot carbon emissions trading work was implemented in 2013, the gap in the carbon lock-in degree between the treatment and control groups were close to zero. However, after implementing the pilot carbon emissions trading work in 2013, the gap increased significantly, and impact trend presented a trend that first increased and then decreased. Based on the test results above, we conclude that the sample satisfies the DID model prerequisites.

4.2.2. Empirical results of the DID

Based on the verification that the sample satisfies the parallel trend test of carbon lock-in, this study uses the fixed-effects DID method to assess the effect of implementing a pilot carbon trading policy. To minimize regression estimation bias and achieve effective comparison between the results, this study selected model (1) without the time and individual fixed effects without control variables, model (2) with individual fixed effects only, and model (3) with individual fixed effects and time fixed effects as a two-way fixed effects model, model (4) with individual fixed effects and the introduction of control variables, and model (5) with two-way fixed effects and the introduction of control variables for estimation. Table 1 presents the results.

Table 1. Differences-in-Differences model regression results.

	(1)	(2)	(3)	(4)	(5)
Treat*post	-0.0382	-0.0382	-0.0382**	-0.0518**	-0.0438***
	(-0.63)	(-1.56)	(-2.10)	(-2.33)	(-2.60)
FDI				-0.256	-1.534***
				(-0.66)	(-5.05)
RCL				-0.259***	-0.138***
				(-8.78)	(-5.30)
cons	2.105***	2.059***	2.180***	2.218***	2.288***
	(105.65)	(286.81)	(166.77)	(109.50)	(125.11)
N	390	390	390	390	390
R2	0.284	0.566	0.760	0.643	0.796
individual fixed	NO	YES	YES	YES	YES
time fixed	NO	NO	YES	NO	YES
control variables	NO	NO	NO	YES	YES

*Notes: t-statistics in parentheses; *p<0.10, **p<0.05, ***p<0.01.*

Our regression results show that the interaction term coefficients of the core explanatory variable become significant at the 5% level after adding time fixed effects to individual fixed effects. This indicates that the omitted variables affect the effect of carbon lock-in over time. Therefore, using a two-way fixed effects model in this study is necessary so the carbon unlock-in effect of carbon emissions trading can be obtained more accurately. After introducing only control variables based on individual fixed effects, we also present a significant negative effect of the carbon trading policy on the degree of carbon lock-in at the 5% level; however, FDI is not significant. This indicates no significant difference in FDI at the provincial level, whereas the level of regional construction has a significant negative effect on degree of carbon lock-in.

Finally, after adding control variables to the two-way fixed-effects model, the interaction term coefficients of the core explanatory variable, which are the most critical concern of this study, are significantly negative at the 1% level. This indicates that the implementation of China's pilot carbon emissions trading' policy has significantly reduced degree of carbon lock-in in the pilot provinces. Regarding control variables, both FDI and RCL have significant negative effects on the level of carbon lock-in, with FDI having a more significant effect. This indicates that technological innovation is vital in carbon unlocking.

4.3. Analysis of regional differences in the carbon unlocking effect of carbon emissions trading

4.3.1. Empirical results of the SCM

Sample data used in this section are consistent with those in the previous section, with 2007–2019 as the SCM study period. The predictor variables were used as control variables for foreign direct investment and regional construction levels, as described in the previous section. The remaining 24 non-pilot regions were used as the control group to optimally weigh the estimated degree of carbon lock-in for the six pilot regions. Considering that carbon trading in the pilot regions of Beijing, Tianjin, Shanghai, and Guangdong officially ran in 2013, and Hubei and Chongqing ran formally in 2014, their actual running time was considered as the year of the policy shock in SCM. Table 2 presents optimal weighting estimates for the six pilot regions and the root mean square percentage error (RMSPE) before policy implementation.

Table 2. Synthetic Weights and Root Mean Square Percentage Error for Each Pilot.

Region	Weights					RMSPE
Beijing	Jiangsu 0.507	Fujian 0.239	Xinjiang 0.19	Hainan 0.048	Shandong 0.015	0.010
Tianjin	Fujian 0.636	Qinghai 0.22	Liaoning 0.115	Hainan 0.028		0.012
Shanghai	Fujian 0.671	Jiangsu 0.231	Xinjiang 0.076	Hainan 0.022		0.002
Hubei	Xinjiang 0.256	Shandong 0.186	Henan 0.139	Zhejiang 0.037	Anhui 0.03	0.026
Guangdong	Shandong 0.431	Fujian 0.408	Hainan 0.142	Yunnan 0.02		0.074
Chongqing	Fujian 0.4	Qinghai 0.236	Hainan 0.094	Guangxi 0.049	Xinjiang 0.025	0.022

Next, pilot regions were synthesized according to the weight of the control group. Fig. 5 presents the comparative trend between the observed carbon lock-in effect values of the six pilot regions and corresponding synthetic estimated carbon lock-in effect values of the six pilot regions. Fig. 5 indicates that the synthetic value of the carbon lock-in degree for Guangdong before policy intervention in the carbon emissions trading pilot was a

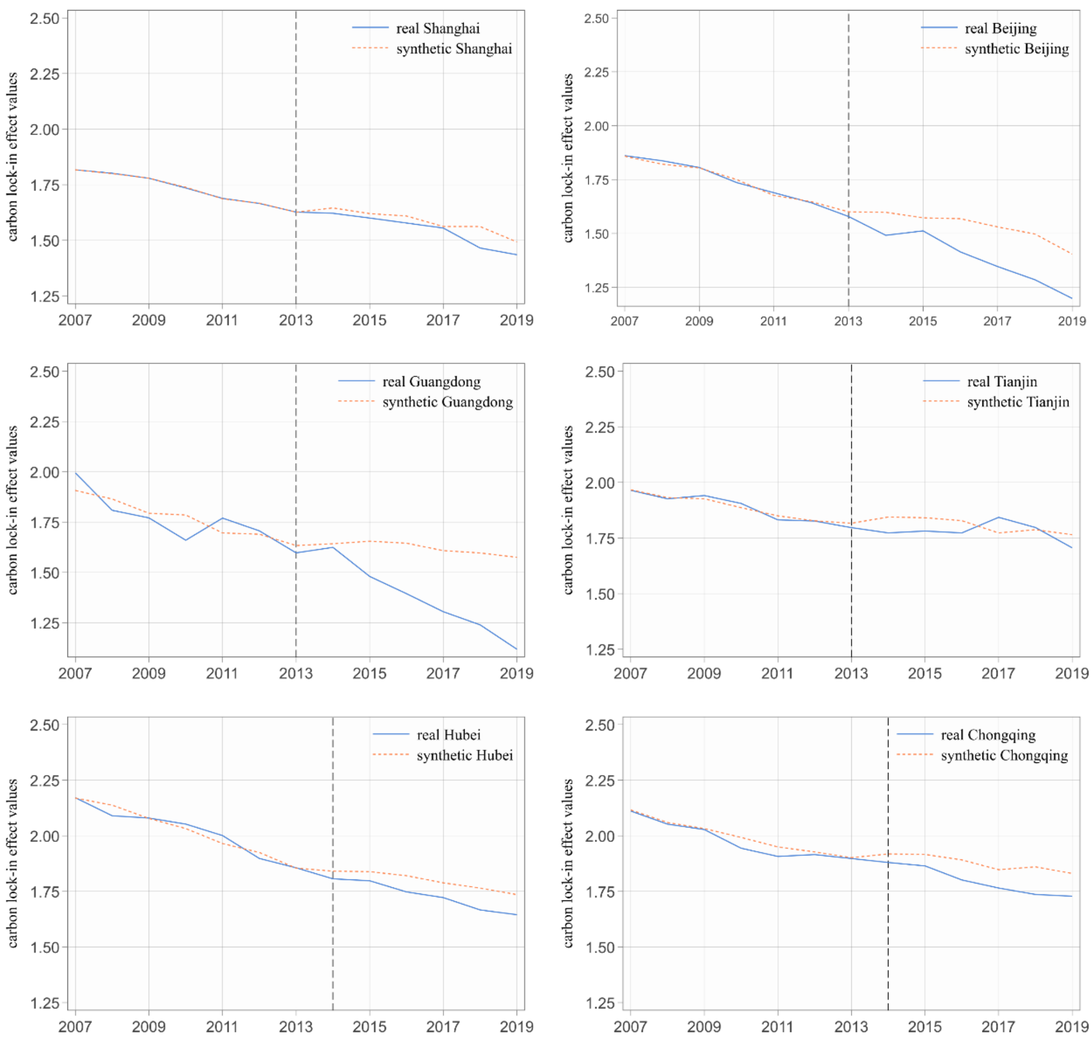


Figure 5. Trends in carbon lock-in effect values: pilot provinces (municipalities) vs. synthetic pilot provinces (municipalities).

relatively poor fit for the actual value. However, the RMSPE of 0.074 was within an acceptable range. The synthetic curve for the remaining five pilot cities before policy intervention was nearly identical to the actual value, which is consistent with the error results in Table 2. From the fitting of the post-policy intervention of the carbon emissions trading pilot, the carbon lock-in degree values were lower than the synthetic values in five of the pilot provinces—Guangdong, Beijing, Chongqing, Hubei, and Shanghai. This indicates that the carbon emissions trading policy has, to some extent, contributed to increasing carbon unlocking in these five provinces. Tianjin had a carbon unlocking effect at the beginning of the policy implementation phase. However, the policy utility became insignificant, and a negative utility emerged in 2016–2018.

Fig. 6 indicates that Guangdong has had the best carbon unlocking effect since the implementation of the carbon emissions trading policy, followed by Beijing, Hubei, Chongqing, and Shanghai with an average carbon unlocking effect. By contrast, Tianjin had the least satisfactory carbon unlocking development. According to Wind data (https://www.wind.com.cn/), by the end of December 2019, the cumulative turnover of carbon allowances in Guangdong Province was 118,982,600 tons. Cumulative turnover was RMB 186.4 million, which ranks first among all pilot cities. Cumulative turnover of carbon allowances in Tianjin was 6,541,100 tons, and cumulative turnover was RMB 87 million, ranking last among all the pilot cities.

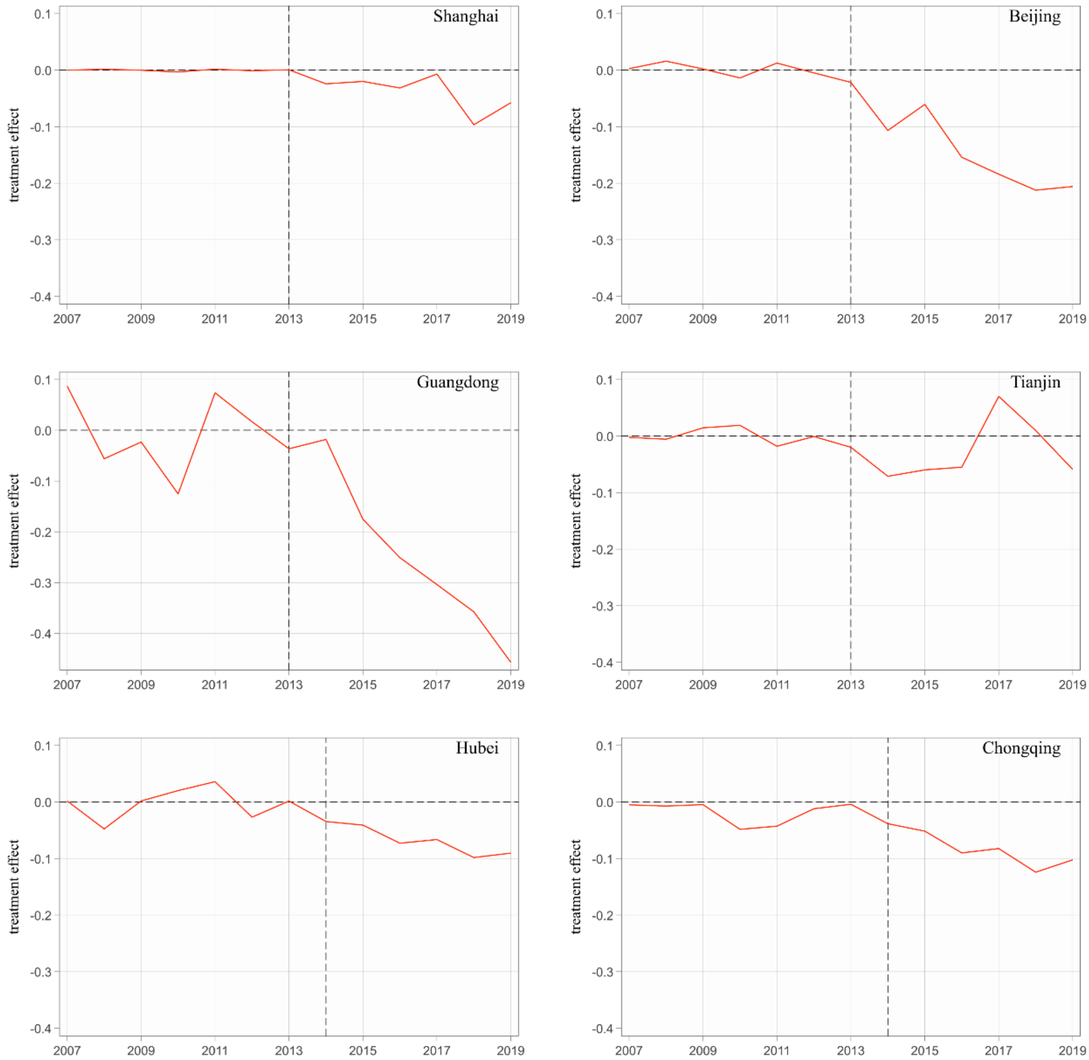


Figure 6. Carbon lock-in effect values gap between pilot provinces (municipalities) and synthetic pilot provinces (municipalities).

SCM results are broadly consistent with the carbon quota trading situation, with provinces with more transactions having better carbon unlocking effects.

4.3.2. Robustness tests

To confirm the validity of the above results and that the estimated policy effects are statistically significantly different from zero, a ranking test is recommended (Abadie et al., 2010). This is used to determine whether the same situation occurs in other provinces, as in pilot provinces, and with what probability. This method assumes that all control group provinces also began implementing carbon trading policies in 2013 or 2014, which constructs a synthetic carbon lock-in for the corresponding provinces using SCM and estimating the policy effect in the hypothetical case. Then, under hypothetical conditions, the actual policy effects generated in the pilot provinces were compared with those generated by control group provinces. If the difference between policy effects is sufficiently large, there is reason to believe that the carbon emissions trading policy effect is significant.

This approach requires a good fit for the degree of synthetic carbon lock-in in each province prior to policy implementation. If a province has a poor fit before policy implementation (i.e., relatively large RMSPE value), even a large difference in the predictor variables obtained later in the policy does not reflect the effect of the policy. Therefore, in this study, cities with abnormal RMSPE values before policy implementation were excluded, and all six pilot regions with the most significant RMSPE values in the control group test were Jiangsu.

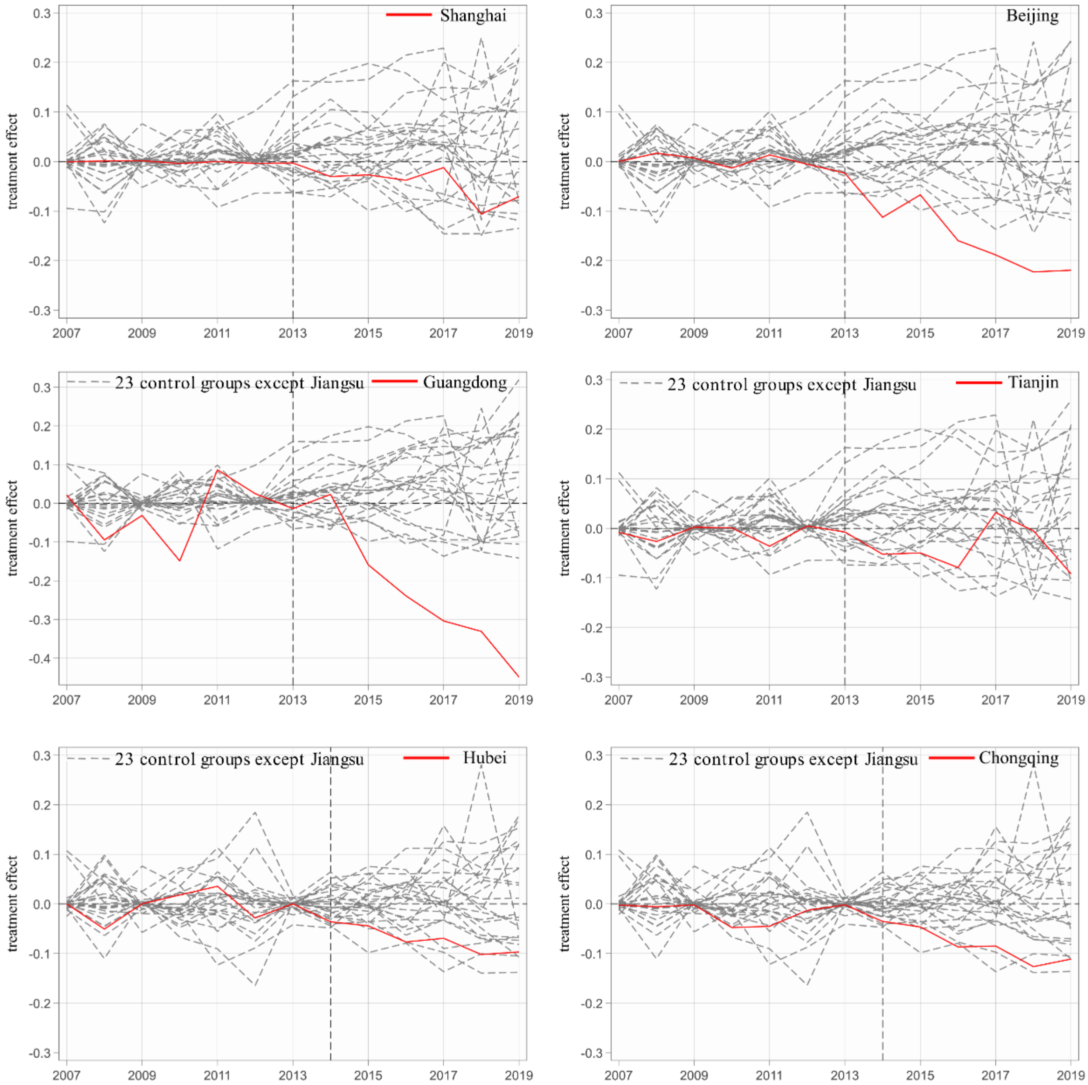


Figure 7. The carbon lock-in effect values gaps in pilot provinces (municipalities) and placebo gaps in 23 control provinces (municipalities).

Fig. 7 presents the results of the robustness test. The implementation of the pilot policy in Beijing has reduced the degree of carbon lock-in. Excluding Jiangsu, the remaining 23 provinces in the sample present a 4.34% (1/23) probability that a significant gap exists in the degree of carbon lock-in between Beijing and the synthetic Beijing and the effect of carbon unlocking in Beijing can be considered significant at the 5% level. Similarly, Guangdong had a 4.34% (1/23) probability of having a large gap between the extent of carbon locking in Guangdong and synthetic Guangdong. The effect of carbon unlocking in Guangdong could be considered significant at the 5% level.

For Hubei and Chongqing, the dashed lines below the solid red line are only two after the policy occurrence, and the calculated probability of the policy effect is attributable to a mistake made by chance being about 8.70% (2/23). Therefore, at the 10% significance level, we can assume that the carbon unlocking effect of the pilot carbon trading policy in Hubei and Chongqing passes the placebo test. However, the carbon unlocking effect of the carbon emissions trading pilot policy does not pass the placebo test, carbon unlocking effect is not significant, and carbon emissions trading policy needs further strengthening.

5. Discussion and Analysis

According to the above analysis, a carbon emissions trading policy can significantly mitigate carbon lock-in. The following will further explore the mechanisms of the impact (i.e., paths of achieved carbon unlocking). As stated in the construction of the carbon lock-in measurement index system in the second part of this study, carbon lock-in is formed through four mechanisms: infrastructure, technology, institution, and social behavior. Therefore, the four carbon lock formation mechanisms were used as intermediary variables to regress carbon lock-in. Fixed input lock-in is not significant in the first stage, and Table 3 lists the regression results after excluding it.

Table 3. Influencing mechanisms of carbon emission trading policy on carbon unlocking.

Variables	Lock	Technique	Institution	Social behavior	Lock
Treat*post	-0.0438***	-0.0671***	-0.0186**	0.0486***	0.00629
	(-2.77)	(-9.34)	(-2.49)	(4.61)	(1.07)
Technique					1.221***
					(29.43)
Institution					1.012***
					(27.01)
Social behavior					1.043***
					(38.48)
_cons	1.913***	0.647***	0.805***	0.0958***	0.208***
	(84.17)	(62.81)	(75.04)	(6.33)	(5.88)
N		390	390	390	390
Province fixed		YES	YES	YES	YES
Year fixed		YES	YES	YES	YES
control variables		YES	YES	YES	YES

*Notes: t-statistics in parentheses; *p<0.10, **p<0.05, ***p<0.01.*

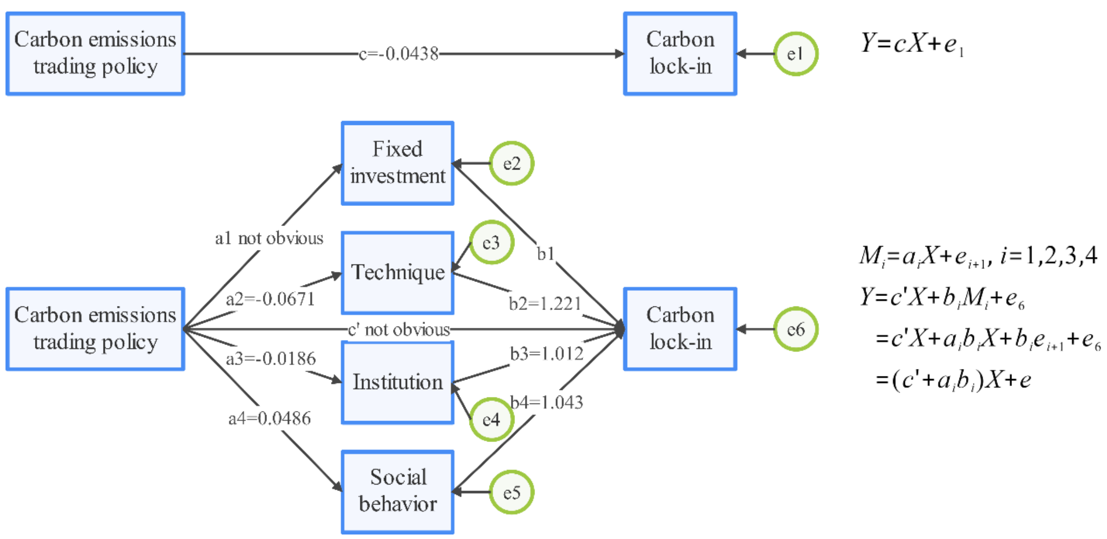


Figure 8. Mechanism analysis framework diagram.

Table 4. The effect values of the mediation effect.

		Coef	Proportion of total effect
Direct effect		0.00629	-0.143607306
	Technique effect	-0.0820***	1.872146119
Indirect effect	Institution effect	-0.0188**	0.429223744
	Social behavior effect	0.0507***	-1.157534247
Total effect		-0.0438**	

*Notes: *p<0.10, **p<0.05, ***p<0.01.*

Table 3 and Fig. 8 indicate that in stage (a), implementing a carbon emissions trading policy significantly reduces technical lock-in and institutional lock-in and increases social behavior lock-in. Referring to existing studies, both EU experience and Chinese attempts confirm that carbon trading effectively promotes innovative low-carbon technologies and carbon reduction (Teixidó et al., 2019; Wang et al., 2021), leading to lower technology lock-in. Government intervention is also key in reducing carbon emissions (Lin and Huang, 2022). Moreover, the policy does not lead to a shift in household lifestyles toward low carbon and even deepens the lock-in of social behavior, which clearly runs counter to our expectations. However, a negative correlation between voluntary action and reduction potential has also been confirmed (Dubois et al., 2019).

In stage (b), technology lock-in, institutional lock-in, and social behavior lock-in significantly increase total carbon lock-in effect. As c' is not significantly different from 0, the mediating effect of carbon emissions trading policy on carbon lock-in is a fully mediated process. Hence, carbon unlocking cannot be performed directly by carbon emissions trading policy. Table 4 results show that carbon trading policies play a mediating role in carbon unlocking by reducing technology lock-in and institutional lock-in by 187.2% and 42.9%, respectively. However, social behavior plays a reverse mediating role of 115.7%. Our results reveal that the transformation of high-carbon infrastructure and social behavior requires additional policies to induce unlocking toward low carbon. Particularly, the extent to which social behavior influences carbon lock-in should not be underestimated.

6. Conclusions and Policy Implications

6.1. Main conclusions

This study used panel data on 17 indicators from 30 provincial-level administrative regions in China from 2007 to 2019 as a research sample to measure the carbon lock-in effect based on the RAGA-PP model. Subsequently, DID and SCM methods are used to empirically analyze the carbon unlocking effect in the pilot cities of carbon emissions trading, leading to the following conclusions:

(1) The overall carbon lock-in trend in China's provinces is declining. Significant interprovincial differences exist in the degree of carbon lock-in in China's regions, presenting a development pattern wherein the carbon lock-in effect is weakest and strongest in the eastern and western provinces, respectively. Level of carbon lock-in governance in the eastern provinces has been leading nationwide. Although the central and western provinces have reached carbon unlocking milestones, a significant gap remains in the eastern provinces.

(2) Among the contributions to the level of carbon lock-in, the top four contributors to the level of carbon lock-in are urban natural gas penetration, state-controlled enterprises level, transaction value in the technical market, and carbon emission intensity of fixed assets, and all of which belong to different criterion levels. Among social behavior indicators, only urban natural gas penetration indicator contributes snificanthighly to the carbon lock-in level. However, reducing the level of residential household energy use is difficult. This shows that, to change the status quo of carbon lock-in, we mainly begin from the initial investment construction and technological innovation, and state-owned enterprises should initiate carbon unlocking.

(3) Implementing carbon emissions trading policies can effectively mitigate the carbon lock-in effect; however, the effect gradually weakens as the number of years of policy implementation increases. This phenomenon indicates that at the beginning of policy implementation, enterprises in each region, out of long-term cost and remuneration considerations, choose to convert to new kinetic energy and replace it with low-carbon infrastructure and other carbon unlocking methods to obtain more future profits. Once companies reduce their carbon emissions to within carbon allowances, they do not conduct further carbon unlocking.

(4) Influenced by the carbon emissions trading policy, degree of carbon lock-in in Guangzhou decreases significantly, and the robustness test indicates the reliability of the results. Beijing, Hubei, Chongqing, and Shanghai also observed reduction in the degree of carbon lock-in after implementing the policy. However, this effect was not particularly pronounced. Carbon unlocking effect in Tianjin remains the least desirable. Degree of carbon unlocking has a specific relationship with the volume of carbon quota trading. Moreover, provinces with large volumes of carbon quota trading have a better carbon unlocking effect. The degree of carbon unlocking may also be closely related to policy differences on a legal basis, coverage of industries and enterprises, carbon quota allocation, penalty mechanisms, and market regulation mechanisms of carbon trading markets in each province.

(5) China's carbon trading policy achieves carbon unlocking by reducing both technology and institutional lock-in impact mechanisms but plays a negative role in social behavior and has little significance in reducing fixed asset lock-in. This may be because carbon trading is a market-based solution for the environment and does not force residents to adopt low-carbon behavior while possibly releasing a large amount of consumer demand. In turn, this increases the lock-in effect of social behavior. Additionally, the policy has a low stimulus to unlock fixed assets because of the high cost of infrastructure and low strength of carbon quotas. Policymakers should additionally adopt policies to avoid the continued shift to carbon-intensive lifestyles by households and incentivize businesses to shift from high-carbon to low-carbon facilities.

6.2. Policy Implications

(1) Strengthen carbon lock-in governance in the western region. China's western region has the highest degree of carbon lock-in, probably because the western region is a significant development and transformation base for China's energy resources. This requires a considerable amount of energy to be sent outwards. Therefore, in the carbon unlocking process, the western region can vigorously develop clean energy sources (e.g., wind and solar power), gradually replacing high carbon emission production energy equipment and strengthening carbon capture and sequestration technologies.

(2) Increase investment in low-carbon scientific research and build low-carbon infrastructure. The government and enterprises should increase the internal expenditure on R&D funds, investment in fixed assets of high-tech industries, and expenditure on science and technology in local financial accounts. To help enterprises advance the R&D integration process, low-carbon technologies must be cultivated, applied, and promoted and low-carbon infrastructure, and carbon unlocking should be constructed and realized.

(3) Promote steady progress in the national carbon emissions trading market. The carbon unlocking effect of the carbon emissions trading pilot study was remarkable. Moreover, it has effectively promoted greenhouse gas emission reduction by enterprises in pilot provinces and cities and mapped out the system, training talent, accumulating experience, and laying the foundation for constructing the national carbon market. On this basis, China should actively promote the construction of the national carbon market, build an institutional system to support the operation of the national carbon market, and steadily develop an implementation plan for quota allocation.

(4) Promote the combination of carbon emissions trading and PHCER and improve the carbon quota system.

Guangdong Province has the best carbon unlocking effect and the largest volume of carbon quota trading among pilot carbon emissions trading regions. Carbon emissions trading in this province has two characteristic highlights: implementation of a combination of paid and free distribution of quotas and the combination with the PHCER. Other provinces can refer to the successful experience of Guangdong Province, and combine their economic development, industrial structure, energy consumption, greenhouse gas emissions, and other characteristics to enrich and activate carbon quota trading transactions.

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Disclosure statement

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

Appendix

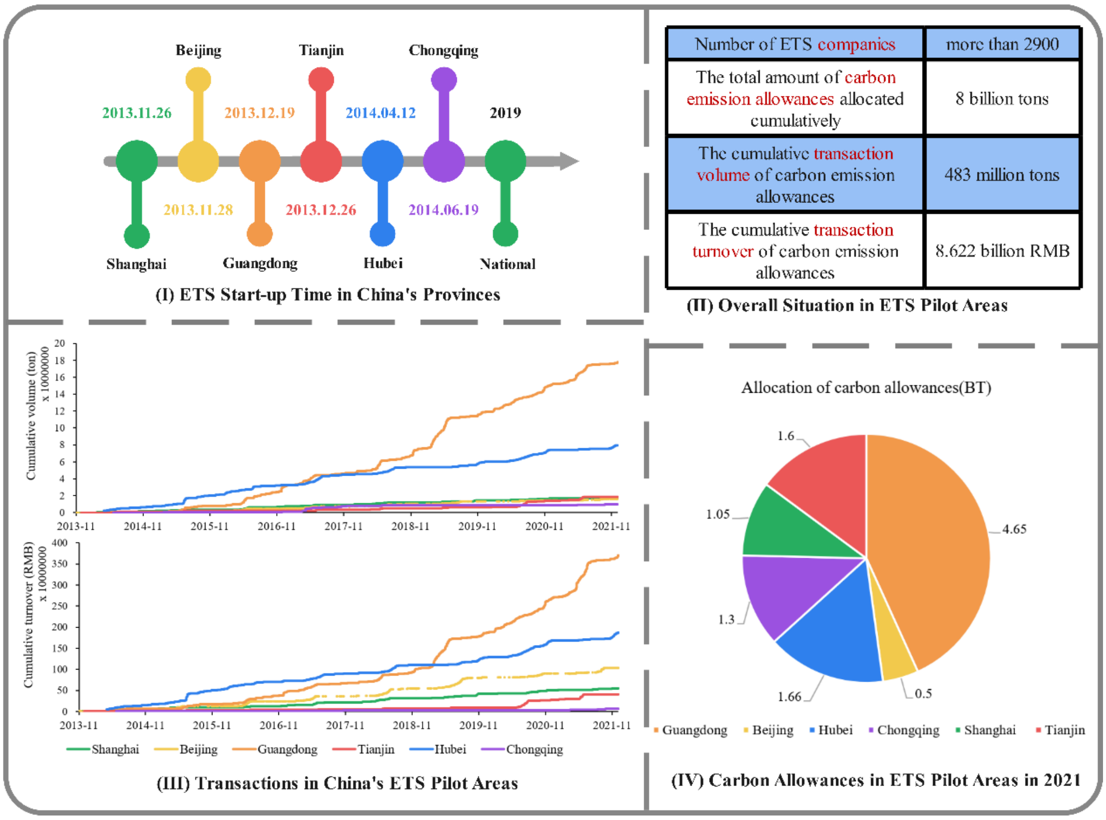

Figure A1. Operation of carbon emissions trading pilot areas in China.

Table A2. Indicator system for evaluating the carbon lock-in effect.

Goal Layer	Criterion Layer	Indicator Layer	Unit	Feature	Source
Integrated indicator system of carbon lock-in assessment	A. Carbon lock-in of fixed input	A1. The ratio of Value-added of the secondary industry to GDP.	%	Positive	China Statistical Yearbooks
		A2. The ratio of total investment in fixed assets in high-tech industries to total investment in fixed assets in society.	%	Negative	China Fixed Assets Statistical Yearbooks
		A3. Carbon emission intensity of fixed assets (the ratio of total CO2 emission to total investment in fixed assets in society).	Ton per 10 000 yuan	Positive	CEADs、China Fixed Assets Statistical Yearbooks
		A4. The ratio of depreciation of fixed assets to GDP.	%	Positive	China Statistical Yearbooks
	B. Carbon lock-in of technique	B1. Energy intensity (the ratio of total energy consumption to GDP).	A ton of standard coal per 10 000 yuan	Positive	China Statistical Yearbooks
		B2. CO2 emission intensity (the ratio of total CO2 emission to GDP).	Ton per 10 000 yuan	Positive	CEADs、China Statistical Yearbooks
		B3. Internal expenditure on R&D.	10 000 yuan	Negative	China Statistical Yearbook on Science and Technology
		B4. Transaction value in the technical market.	100 million yuan	Negative	China Statistical Yearbooks
	C. Carbon lock-in of institution	C1. Scientific expenditures of the local financial accounts expenditure.	100 million yuan	Negative	China Statistical Yearbooks
		C2. The number of professional and technical personnel in scientific research in state-owned institutions.	Person	Negative	China Statistical Yearbook on Science and Technology
		C3. The ratio of investment in the treatment of environmental pollution to GDP.	%	Negative	China Statistical Yearbook on Environment
		C4. State-controlled enterprises level (The ratio of total assets of state-owned industrial enterprises above designated size to the total assets of industrial enterprises above designated size).	%	Positive	China Statistical Yearbooks
	D. Carbon lock-in of social behavior	D1. Urbanization level (the ratio of urban population to the total population)	%	Positive	China Statistical Yearbooks
		D2. Per capita disposable income of urban residents.	Yuan per capita	Positive	China Statistical Yearbooks
		D3. The volume of passenger transportation.	100-million-person kilometers	Positive	China Statistical Yearbooks
		D4. Urban natural gas penetration.	%	Negative	China Statistical Yearbooks
		D5. Civilian automobile ownership.	10 000 unit	Positive	China Statistical Yearbooks

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