Evaluation of the Emission Reduction Effects of China's Carbon Emissions Trading Pilot Scheme

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Abstract

This study evaluates the impact of China's carbon market trading the reduction of carbon dioxide emissions, using Chinese provincial panel data from 1998 to 2017. The study found that (1) Carbon trading contributed to the reduction of carbon dioxide emissions in the pilot areas. However, due to differences in economic development and industrial structures, the impact was more pronounced in Tianjin, Shanghai, Hubei, and Chongqing. (2) The results show that the carbon trading regression coefficients for Beijing and Guangdong are significantly negative using the difference-in-difference method. This indicates that the conclusion of carbon market trading's role in reducing carbon dioxide emissions is more robust. (3) Carbon emissions trading promotes the reduction of carbon dioxide emissions through economic incentives and technological innovation. Based on these research conclusions, this article offers the following policy recommendations: When expanding the carbon emissions trading pilot to the entire country, the unique characteristics of each region should be fully considered, and the autonomy of regional pilots in formulating trading rules should be reserved. Additionally, the government should expedite the development of supporting policies for the operation of the carbon market and promote the optimization of the regional industrial structure and the green development of the economy.

Keywords: Carbon emissions, Trading pilot system, China, Verification

1. Introduction

In September 2020, during the general debate of the 75th United Nations General Assembly, Chinese President Xi Jinping stated that China will strive to reach the peak of national carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060. As China's economy enters a new phase, optimizing and upgrading the industrial structure and promoting green economic

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development have become key priorities. Simultaneously, market-based policy instruments, including carbon trading, are expected to play a crucial role in reducing emissions in this new era of peak emissions targets. In 2013, China launched its pilot carbon markets, beginning with trading in Shenzhen, Beijing, Shanghai, Hubei, Chongqing, Tianjin, Guangdong, and other provinces. Over the 8 years of pilot programs, nearly 3,000 emission units participated, with a total quota volume of 406 million tons Carbon dioxide equivalent, the turnover is about 9.28 billion yuan (Ministry of Ecology and Environment, 2020). By the end of 2017, China announced plans to establish a unified national carbon market, with the power industry as the first sector to launch transactions. Once operational, the Chinese carbon market is expected to surpass the EU ETS as the world's largest carbon trading market (International Energy Agency, 2020). During the pilot period of the carbon market trading, did it effectively contribute to emissions reductions? What impact did carbon trading have on the pilot areas? This article reviews the carbon market trading pilots from 2013 to 2017 and aims to answer these questions.

2. Literature review

In recent years, both domestic and foreign scholars have conducted extensive empirical research and analysis on the effectiveness of carbon market transactions. In the context of EU ETS, research has shown that the carbon emission trading system can reduce corporate carbon emissions (Brouwers et al., 2018) and sectoral carbon emissions (Borghesi et al., 2015). In the context of pilot trading in China's carbon market, studies have found that carbon market trading policies can reduce carbon emissions (Dong et al., 2019) and carbon emission intensity (Zheng et al., 2019), as well as promote the optimization of industrial structure (Song & Kong, 2019; Tan & Zhang, 2018) and regional environmental dividends (Huang et al., 2018).

In the literature on policy analysis of carbon trading market, the analytical techniques can be divided into two categories. First, the single difference method compares carbon dioxide emission before and after the implementation of carbon trading pilot policies (Xiao, 2017; Zheng, 2014).

This method can intuitively compare the carbon dioxide emissions between regions before and after the policy is implemented. However, this method has limitations, as it does not sufficiently analyze the factors affecting carbon dioxide emissions. The single-difference analysis cannot account for other factors, such as economic and policy variables, that may influence emissions during the carbon trading period. Second, the difference-in-differences method is often used to evaluate pilot transactions (Huang et al., 2018; Zhou et al., 2019; Zhang et al., 2019). This method is a widely applied evaluation technique. In the tradition of the double-difference method in the selected control group was compared with the treatment group policy, based on a counterfactual framework to evaluate policy changes occur and the factors observed in both cases does not occur. However, the conventional method cannot efficiently capture the differing characteristics of the treatment and control group. For example, when 24 provinces are used as a control group for the pilot areas (expect for the existing pilots), the method cannot effectively eliminate the influence of pre-existing policies or geographical difference.

Moreover, some studies failed to pass the parallel trend hypothesis test, which undermines the robustness of their conclusions. To address this limitation, the propensity score matching double-difference method improves the traditional approach by pre-selecting a reference group that closely matches the control group, optimizing the matching process. However, PSM-DID has strict conditions of use, and its matching results can only be optimized with a large sample size. The seven years of trading data from the six pilot regions do not meet the sample size requirements for this method.

As a quasi-natural experiment, the key challenge is to accurately simulate the condition of a policy-affected area in the absence of policy intervention, which is critical for establishing a counterfactual framework. In 2003, Abadie and Gardeazabal introduced the synthetic control method, which addresses the limitations mentioned above. A virtual control group is created by screening and synthetic control variables to match the evolution of the policy-affected area before the policy is implemented. Synthetic control analysis has been applied in studies of real estate tax pilot (Liu & Fan, 2013; Liu & Zeng, 2018), low-carbon city pilots (Lu, 2017), administrative division adjustments (Zhang et al., 2017), and carbon market trading pilots (Liu et al., 2019). When constructing a virtual control group, weights are applied to measure the distance between predictors, minimizing the influence of supervisory factors on the evaluation of policy effects. The weight setting also reflect the contribution of provinces that are not part of the carbon trading pilots in constructing the counterfactual state. Based on the above analysis, this article will use the synthetic control analysis method to evaluate the effectiveness of China's carbon market trading pilots, using panel data from 2008 to 2017. We propose the following hypothesis regarding the emission reduction effect of the carbon emission trading policy: China's carbon emission trading pilot policy can reduce carbon dioxide emissions in the pilot areas.

3. Model and data

3.1 Synthesis control method

This paper applies Abadie's synthetic control method to analyze the emission reduction effects of carbon trading pilots (Abadie & Garbeazadal, 2003; Abadie et al., 2010). The Analysis proceeds with the following steps: (1) selection of predictors and determination of the weight values based on the distance between them; (2) fitting the six pilot provinces with their corresponding control provinces, synthesized according to the weight; and (3) comparing the carbon emissions in the pilot provinces and municipalities with those in the synthetic control provinces and cities to evaluate the effects of carbon trading policies.

In this study, the dependent variable is carbon dioxide emissions. In a given set of K +

1 region, the carbon emissions panel data for period T $\alpha_{it}^{Y}(i\in[1,1+K]\,;\,t\in[1,T])$, represents the carbon emissions in the i^{th} region after it became part of the carbon trading pilot at time t, and $\alpha_{it}^{U}(i\in[1,1+K]\,;\,t\in[1,T])$ represents the carbon emissions in the i^{th} region before it became part of the trading pilot. Suppose the policy start time $t=T_0$. Then, for the period [1, T_0], carbon emissions in the region will not be affected by the carbon trading policy, meaning at this time $\alpha_{it}^{Y}=\alpha_{it}^{U}$. For the period [$T_0$, T], carbon emissions in the region will be affected by the carbon trading policies. The effect is measured as the difference: effect $=\alpha_{it}^{U}-\alpha_{it}^{Y}$. α_{it}^{U} is the observable data, but α_{it}^{Y} the quantity that needs to be estimated. According to the factor model proposed by Abadie et al., (2010), α_{it}^{Y} the estimation formula is as follows:

$$\alpha_{it}^{Y}=\gamma_t+\beta_t P_i+\delta_t\theta_i+\varepsilon_{it} \tag{1}$$

In formula (1), γ_t represents the time fixed effect, capturing unobservable influences that vary over time but are consistent across regions. P_i is the (K*1) -dimensional covariate, representing control variables unaffected by the low-carbon pilot policy, such as regional characteristics and baseline economic conditions. β_t is the (1*K) -dimensional parameter vector to be estimated. Δ_t represents the (1*R) dimensional unobservable regional fixed effects, while θ_I is the (R*1) dimensional parameter vector associated with these fixed effects, to be estimated. to be estimated. E_{it} captures unobservable short-term shocks, assumed to have a mean value of zero at the regional level, ensuring no systematic bias in the residuals. In order to determine α_{it}^{Y}, a (N * 1)-dimensional weight vector $W=(W_2,W_3,\ldots,W_{n+1})$ is introduced, where $W_k\geq 0$, $K\in(2,3,\cdots,n+1)$. The weight vector W measures the fit between the synthetic control group and the observed characteristics of the treatment group, aligning the control region's carbon dioxide emissions with those of the treated region. For each reference group region, variable weighting values can be obtained to:

$$\sum_{n=2}^{n+1}W_n\alpha_{ni}=\gamma_t+\beta_t\sum_{n=2}^{n+1}W_nP_{ni}+\delta_t\sum_{n=2}^{n+1}W_n\theta_n i+\sum_{n=2}^{n+1}W_n\varepsilon_{ni} \tag{2}$$

Equation (2) describes how the synthetic control is constructed by assigning weights (W_n) to the predictors (α_{ni}) of the control group regions. The goal is to replicate the characteristics of the treatment region before the policy intervention.

Assuming weight vectors ($W_2^*,W_3^*,\ldots,W_{n+1}^*$) are assigned to each control group region, such that they replicate the treated region's characteristics as closely as possible:

$$\underbrace{\begin{bmatrix}\alpha_{21} & \alpha_{31}\cdots & \alpha_{n+1\,1}\\ \vdots & \ddots & \vdots\\ \alpha_{2T0} & \alpha_{3T0}\cdots & \alpha_{n+1\,T0}\end{bmatrix}}_{X_0}\underbrace{\begin{pmatrix}W_2^*\\ W_3^*\\ \vdots\\ W_{n+1}^*\end{pmatrix}}_{W}=\underbrace{\begin{pmatrix}\alpha_{11}\\ \alpha_{21}\\ \vdots\\ \alpha_{n+1\,T0}\end{pmatrix}}_{X_1} \tag{3}$$

The predictors for each control region are represented by matrix X_0, while the predictors for the treated region are represented by vector X_1. The weight vector W minimizes the distance between $X_0\,W$ and X_1, ensuring a close match.

The average of the respective other predictors of Chinese pilot regions referred to as non-matrix X_0 (K * N-dimensional matrix, the subscript 0 indicates "Control Region") wherein the first N ranked N^{th} respective area values. We hope that the weight w makes X_0w as close to X_1 as possible; that is, after weighting, the characteristics of the composite control area are as close as possible to the processing area. The quadratic form is used to measure the distance between the treated region's predictors (X_1) and the weighted predictors of the control regions ($X_0\ W$). Each predictor in X_1, is assigned a weight in the distance function based on its predictive ability, as follows:

$$\min_{w}(X_1 - X_0w)'\ V(X_1 - X_0w) \tag{4}$$

The weight vector W satisfies the following conditions: $W_n \geq 0, n = 2,3,\ldots,n+1$ *and* $\sum_{n=2}^{n+1} W_n = 1$. The matrix V is a (K*K) diagonal matrix that assigns different importance to each predictor based on its predictive ability. Denote the optimal solution of this minimization problem as $w^*(V)$. The optimal V is selected by minimizing the Mean Squared Prediction Error (MSPE), which measures the average squared difference between the predicted emissions ($Z_0\ W^*(V)$) and the actual emissions (Z_j) of the treated region during the pre-policy period. Specifically, Z_1 is the (19*1)-dimensional column vector, which contains the carbon dioxide emissions of the pilot area from 1998 to 2017, and Z_0 is the (19*R)-dimensional matrix, where each column corresponds to the carbon dioxide of the corresponding region in 1998–2017 Emissions. The vector $Z_0\ w^*$(V) is used to predict Z_1. The optimal V minimizes the Mean Squared Prediction Error (MSPE), calculated as the average of the squared prediction errors across all pre-policy periods:

$$\min_{w} \frac{1}{37}\big(Z_1 - Z_0\ w^*(V)\big)'V(Z_1 - Z_0w^*\ (V)) \tag{5}$$

If the synthetic control w^* accurately replicates the economic characteristics and the outcome variables of the treated area prior the intervention, the following synthetic control estimator can be defined (Synthetic Control Estimator):

$$\widehat{\mu_{1t}} = \alpha_{1t} - \sum_{N=2}^{N+1} W_n^* \alpha_{nt}, t \in [T_0 + 1, \ldots, T] \tag{6}$$

In Equation (6), $\widehat{\mu_{1t}}$ represents the estimated effect of the intervention at time t. The term α_{1t} is the observed outcome for the treated unit, while $\sum_{N=2}^{N+1} W_n^* \alpha_{nt}$ represents the synthetic control group's weighted outcome. This difference isolates the policy's effect on the treated area.

The study further demonstrates that, under regular conditions, if the synthetic control w^* fully replicates the characteristics of the treated area and the outcome variables prior to the intervention, then as the number of pre-intervention periods (T_0) approaches infinity, the synthetic control estimator becomes asymptotically unbiased (Abadie et al., 2010).

3.2 Data

(1) Carbon dioxide calculation and selection of control variables

To ensure the synthetic control closely match pilot emissions in 2013 and to enhance the reliability of the analysis, this study uses a sample time from 1981 to 2017. This article examines the effect of carbon trading pilots on carbon emissions, so we choose carbon dioxide emissions (CAE_{it}) as the explained variable. Carbon dioxide emissions in this study are calculated based on fossil fuel emissions. The IPCC (2006) provides a method for the calculation, is calculated as follows:

$$CO_2 = \sum_{i=1}^{7} E_i * S_i * F_i \tag{7}$$

In this equation:

CO_2: Estimated value of carbon dioxide emissions.

i: Represents the seven types of fossil fuels: coal, coke, gasoline, kerosene, diesel, fuel oil, and natural gas.

E_i: Consumption of fossil fuels.

S_i Conversion coefficient to standard coal.

F_i Carbon emissions coefficient for each fuel type.

Based on relevant literature evaluating emission reduction effects, this study selects the following predictive variables:

(1) Economic development level (GDP_{it}): Captures the impact of economic development on carbon dioxide emissions, measured using GDP.

(2) Industrial structure (SEI_{it}, THI_{it}): Reflects the regional industrial structure, using the share of the secondary and tertiary industries in GDP.

(3) Urban population ($URPOP_{it}$): Represents the ratio of the urban population to the total population at the end of the year.

(4) R&D investment case (RDR_{it}): Accounts for regional R&D investment as a percentage of GDP.

(2) Data select

This article selects 30 provinces (municipalities and autonomous regions)[3] in China, using panel data from 1998 to 2017. The panel data is used as the initial sample. The seven carbon trading pilot provinces (municipalities directly under the central government, collectively referred to as provinces from now on) were established in China in 2013, including Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen, are used as the experimental

[3] Based on the availability of data, the research sample of this article is set to exclude 30 provinces, municipalities and autonomous regions of Tibet, Hong Kong, Macau, and Taiwan.

group. The remaining non-pilot provinces are used as the control group. Since Shenzhen is not a province or municipality directly under the central government, it is merged with Guangdong Province for the analysis. The original data are sourced from statistical yearbooks and official websites published by the National Bureau of Statistics of China, covering the provinces, municipalities, and autonomous regions.

4. Evaluation of the policy effects of carbon trading pilots on carbon dioxide reduction

4.1 Weight of synthetic control area

This study constructs synthetic control regions for the six pilot trading regions using predictors such as GDP, industrial structure, R&D investment intensity, urban population, and carbon dioxide emission data from 1998 to 2012. The weights are selected based on the criterion of minimize the mean squared error (MSE) between the carbon dioxide emissions of the pilot provinces and their corresponding synthetic control regions before the start of carbon trading. A higher weight assigned to a province in the control group indicates greater similarity in characteristics to the corresponding pilot province (Table 1). In the synthetic control analysis, Heilongjiang Province contributes the highest weight to the synthetic regions for Beijing, Shanghai, and Chongqing regions. Similarly, Liaoning Province contributes the largest weight to the synthetic regions for Hubei and Guangdong regions, while Gansu Province has the highest

Table 1 The weight of the remaining provinces that constitute the synthetic control province

	Beijing	Tianjin	Shanghai	Hubei	Guangdong	Chongqing
Hebei	0	0	0	0	0.229	0
Shanxi	0	0	0	0.116	0	0
Inner Mongolia	0	0.013	0	0	0	0
Liaoning	0	0	0.289	0.492	0.639	0
Jilin	0	0.029	0	0.19	0	0.244
Heilongjiang	0.557	0.227	0.671	0.044	0	0.391
Jiangsu	0	0	0	0	0	0
Zhejiang	0	0	0	0	0	0
Anhui	0	0	0	0	0	0
Fujian	0	0	0	0	0	0
Jiangxi	0	0.158	0	0.005	0	0.19
Shandong	0	0	0	0	0.132	0
Henan	0	0	0	0	0	0
Hunan	0	0	0	0	0	0
Guangxi	0	0	0	0	0	0
Hainan	0.443	0	0	0	0	0
Sichuan	0	0	0	0.001	0	0
Guizhou	0	0	0	0.143	0	0
Yunnan	0	0	0	0	0	0
Shaanxi	0	0.001	0	0	0	0
Gansu	0	0.411	0	0	0	0
Qinghai	0	0.162	0	0.009	0	0.175
Ningxia	0	0	0	0	0	0
Xinjiang	0	0	0	0	0	0

weight in the synthetic region for Tianjin.

Table 1 presents the weights assigned to provinces in the control group for constructing synthetic control regions corresponding to the pilot regions (Beijing, Tianjin, Shanghai, Hubei, Guangdong, and Chongqing). A higher weight indicates greater similarity in characteristics between the control province and the pilot region, based on predictors such as GDP, industrial structure, urban population, and R&D investment. Heilongjiang Province plays a significant role in constructing the synthetic control regions for Beijing (weight: 0.557), Shanghai (weight: 0.671), and Chongqing (weight: 0.391), indicating high similarity in characteristics to these pilot regions. Liaoning Province contributes substantially to the synthetic control regions for Hubei (weight: 0.492) and Guangdong (weight: 0.639), reflecting its close alignment with these regions in terms of predictors. Gansu Province holds the largest weight (0.411) for the Tianjin synthetic control region, signifying its significant similarity to Tianjin.

4.2 Emission reduction effects of carbon trading pilots

The evolution trends of carbon emissions for the pilot regions and their corresponding synthetic control regions are shown in Figure 1. The vertical dotted line in Fig. 1 marks the start of carbon trading pilot polies in 2013. The period to the right of the dotted line represents the post-implementation phase of the carbon trading pilot. In Figure 1, the solid curve represents the actual carbon dioxide emissions of the pilot provinces, while the dotted curve shows the emissions of their synthetic control regions. The results indicate that all pilot regions, except Beijing, exhibit good features matching between actual and synthetic emissions before the implementation of the pilot. In Beijing, a significant drop in carbon dioxide emissions is observed starting in 2011. This can be attributed to its unique industrial structure, where more than 70% of GDP is derived from the tertiary sector. Additionally, Beijing's special administrative and economic status makes it challenging to achieve a perfect fit using the weighting of other provinces and cities. In Guangdong, carbon dioxide emissions and the corresponding synthetic control region began to diverge in 2011. However, by 2016, the two trends nearly converged. The specific reasons for this convergence will be analyzed in a later chapter. The remaining four pilot regions (Tianjin, Shanghai, Hubei, and Chongqing) met the required criteria. Prior to the implementation of the carbon trading mechanism, actual carbon dioxide emissions closely matched those of the synthetic control regions, demonstrating the effectiveness of the synthetic control method in fitting the actual emissions. As a result, further analysis was conducted on Tianjin, Shanghai, Hubei, and Chongqing to investigate the impact of the carbon trading mechanism.

In Beijing and Guangdong, the emission curve for the pilot regions began to diverge from their synthetic control regions between 2011 and 2013. Although the carbon trading pilots officially launched in 2013, the National Development and Reform Commission issued a notice in October 2011 to approve the initiation of carbon trading in seven pilot provinces and cities. This

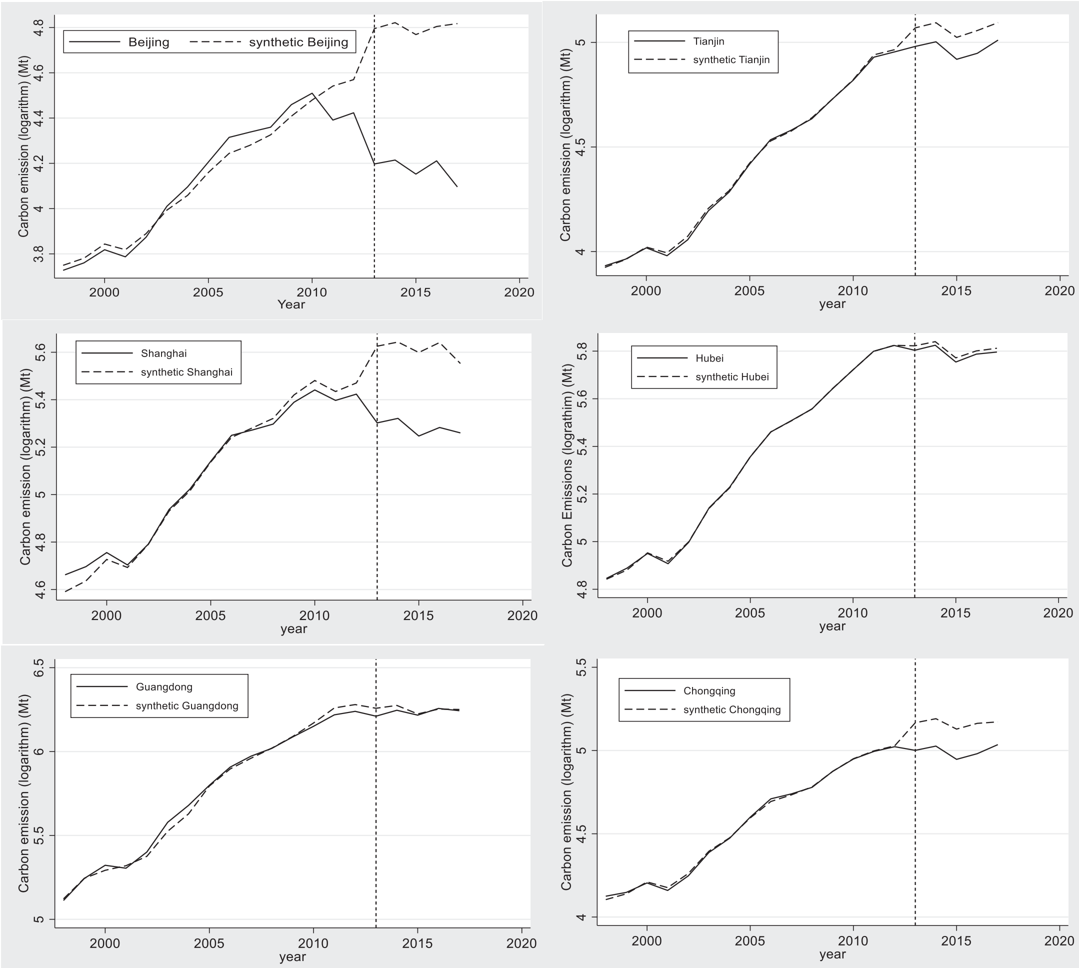

Fig. 1 Carbon dioxide emissions (Mt) of each pilot area and its corresponding combined control province

early preparation encouraged enterprises in the pilot areas to begin reducing emission before the official implementation of the policy. Following the divergence, the carbon dioxide emissions in the pilot regions consistently fell below the emission of their corresponding synthetic control regions. Although the magnitude of the reduction varied across regions, the carbon dioxide emissions in the four pilot regions remained lower than those in the synthetic control regions, demonstrating the effectiveness of the carbon trading pilot policy in reducing emissions.

4.3 Validity check of the carbon trading pilot policy

This section examines the validity of the carbon trading pilot policy using a placebo test and evaluates the effectiveness of the synthetic control method (Abadie et al., 2010).

(1) Placebo test

The placebo test aims to determine whether the observed reductions in carbon dioxide emissions in the four pilot regions are due to accidental common factors rather than the carbon trading pilot policy. To rule out this possibility, a placebo test was conducted to analyze the effectiveness of the carbon trading policy.

The method involves selecting a province that was not a carbon trading pilot during the sample period and assuming it underwent the same policy intervention in the same year as the pilot areas. Using the synthetic control method, we then compare the observed differences in emissions for the placebo region with those of pilot regions. If the difference in emissions for the placebo region are smaller than those observed for the pilot regions, the policy result is valid. Otherwise, they are invalid. The placebo regions were selected based on the provinces with the highest weights in the synthetic control provinces for each region, as shown in Table 1. These include Tianjin-Gansu, Shanghai-Heilongjiang, Hubei-Liaoning, Chongqing-Heilongjiang. Due to the significant weights assigned to Heilongjiang Province for Beijing, Shanghai, and Chongqing, it was selected as the placebo region for these areas. For clarity, we label them as Shanghai-Heilongjiang 2 and Chongqing-Heilongjiang 3. As Liaoning did not have a satisfactory synthetic match for Hubei before 2013, Guizhou, which had the second-highest weight for Hubei, was selected as the placebo region.

Figure 2 illustrates the actual and synthetic carbon dioxide emissions (in megatonnes, Mt)

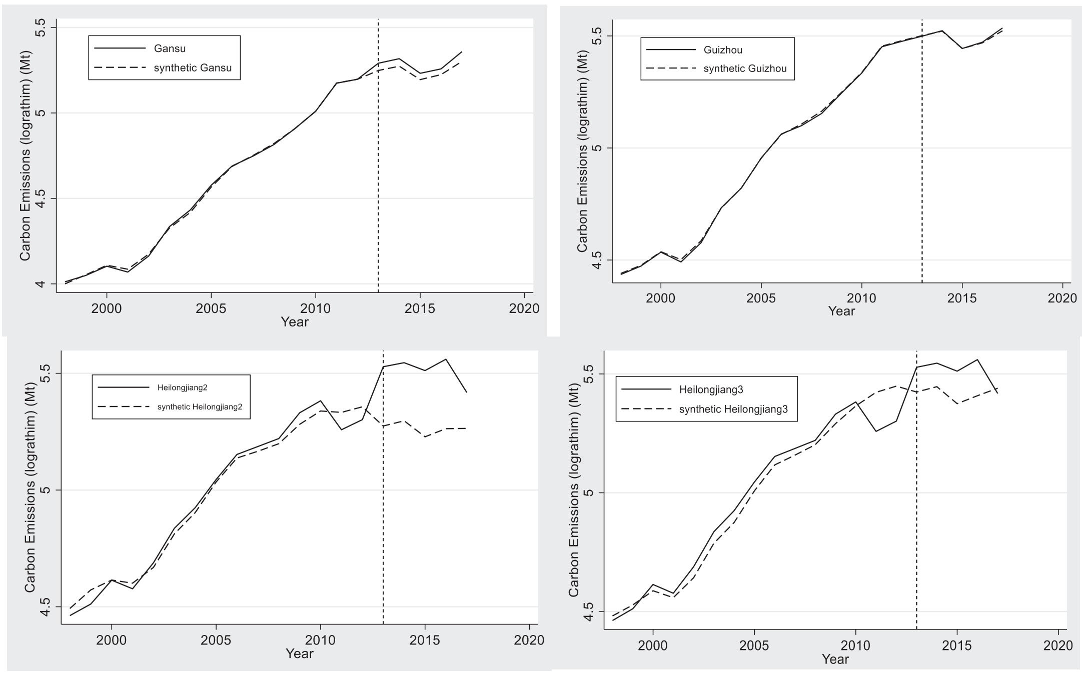

Fig. 2　Carbon dioxide emissions (Mt) of placebo regions and their corresponding synthetic control provinces

for three placebo regions: Gansu, Heilongjiang, and Guizhou. The X-axis represents the timeline from 2000 to 2020, while the Y-axis shows carbon dioxide emissions. Solid lines indicate actual emissions in the placebo regions, and dashed lines represent emissions for their synthetic control regions. The vertical dotted line marks the introduction of the carbon trading pilot policy in 2013.

Before 2013, the solid and dashed lines for each placebo region align closely, suggesting a good pre-treatment fit between the actual and synthetic emissions. After 2013, the solid lines remain above the dashed lines, indicating that the placebo regions did not experience significant reductions in emissions. This result contrasts with the observed trends in pilot regions, where emissions consistently fell below the synthetic control regions, validating the robustness of the policy's effects.

(2) Sorting test

To further evaluate the statistical significance of the estimated policy effect, this study employs a ranking method, similar to a rank test, as outlined by Abadie et al., (2010). The method involves randomly selecting non-pilot provinces and assuming they were subject to the policy treatment effect in 2013. Using the synthetic control method, this study constructs synthetic carbon dioxide emission values to calculate a series of random policy effects, defined as the difference between the actual and synthetic values. The policy effect of the pilot provinces is then compared to the distribution of random errors. If the policy effect for the pilot provinces is significantly larger (in absolute value) than those for the randomly selected provinces, the result is deemed statistically significant. This study uses the Mean Square Prediction Error (MSPE) to measure the differences in carbon trading effects between the control pilot province its synthesis counterpart. The MSPE formula is defined as follows:

$$MSPE = \frac{1}{T_0}\sum_{t=1}^{T_0}(\alpha_{1t} - \sum_{k=2}^{k+1} w_k * \alpha_{kt})^2 \tag{8}$$

Where:

T_0 : Pre-policy period,

α_{1t} : Actual emissions in the pilot region at time t_1 ,

w_k : Weight assigned to the K^{th} control region,

α_{kt} : Emissions in the K^{th} control region at time t.

Non-pilot provinces are excluded from the ranking test under the following conditions:

1. Provinces with poor pre-treatment fit, where differences between actual and synthetic values in the post-treatment period may arise from fitting errors rather than policy effects. Provinces with an MSPE greater than twice that of the pilot provinces are excluded from the analysis (Abadie et al., 2010).
2. Only provinces with positive weights during the construction of synthetic provinces, and

no more than two provinces with zero weights, are selected (Tan & Zhang, 2018). As Beijing and Guangdong did not achieve a good pre-treatment fit with their synthetic provinces, the effectiveness test was conducted only for four regions: Tianjin, Shanghai, Hubei, and Chongqing. The solid black line in the figure indicates the pilot area, and the solid gray line indicates the non-pilot region.

The sorting test results further validate the robustness of the carbon trading pilot policy's emission reduction effects, demonstrating that the observed reductions are statistically significant and not attributable to random factors.

As shown in the figures, the differences between the actual carbon dioxide emissions and the interpolated values for the four regions are notably larger compared to the policy effects observed in the non-pilot provinces within the respective control groups. This indicates that the pilot provinces exhibit significantly different trends in emission reductions compared to the non-pilot provinces. The distinct differences in synthesis errors between the pilot and non-pilot provinces validate the significant policy effects of carbon trading pilots.

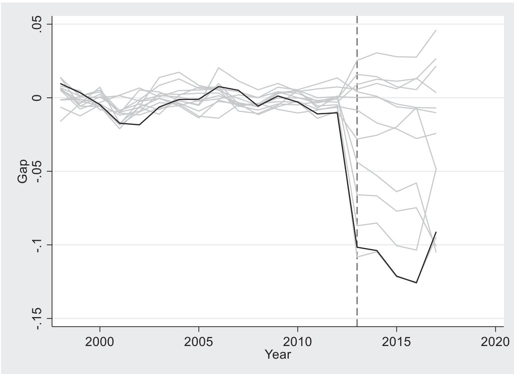

Fig. 3　Effectiveness analysis of Tianjin

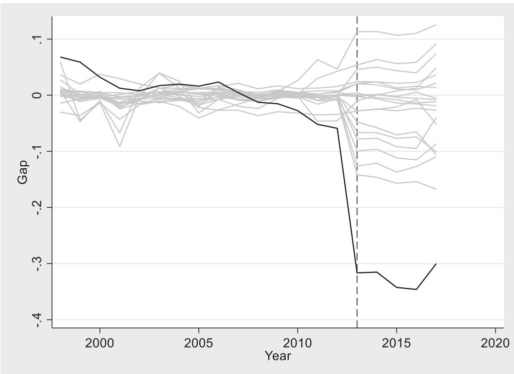

Fig. 4　Effectiveness analysis of Shanghai

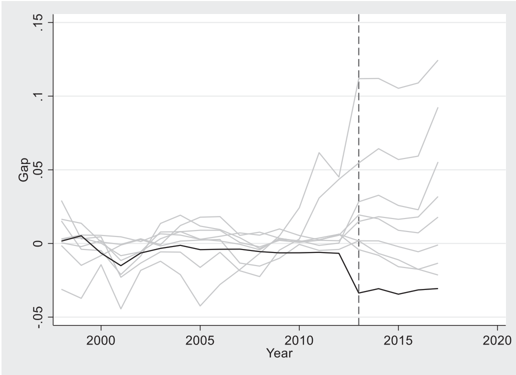

Fig. 5 Effectiveness analysis of Hubei

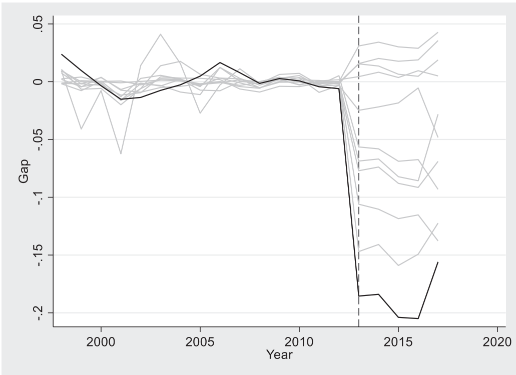

Fig. 6 Effectiveness analysis of Chongqing

4.4 Analysis of the policy effects of Beijing and Guangdong

This section employs the Synthetic Control Method-Difference-in-Differences (SCM-DID) approach to evaluate the robustness of carbon emission reduction effects in the Beijing and Guangdong pilot regions. Using the synthetic control method, Beijing and Guangdong are analyzed as pilot regions to compare their emission trends against those of non-pilot regions. A dual analysis framework is employed to determine whether the carbon trading policy has effectively reduced emissions in these regions. The analysis is conducted using a two-way fixed effects model, which accounts for both temporal and regional variations in emissions:

$$Emission_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 T_{it} + \beta_3 (D_{it} * T_{it}) + \varepsilon_{it} \tag{9}$$

Where:

$Emission_{it}$: Carbon dioxide emissions in region i at time t,

D_{it}: Binary variable indicating whether region i is part of the pilot program (1 for pilot regions, 0 otherwise),

T_{it} : Binary variable for the post-treatment period (1 for years after 2013, 0 otherwise),

$D_{it}*T_{it}$: Interaction term measuring the combined effect of the pilot program and the post-treatment period,

ε_{it} : Error term capturing unobserved factors,

$\beta_0, \beta_1, \beta_2, \beta_3$: Coefficients to be estimated.

This model allows for the isolation of the causal effects of carbon trading on emissions by controlling for region-specific characteristics (D_{it}) and time-specific trends (T_{it}), while the interaction term ($D_{it}*T_{it}$) captures the policy effect.

The SCM-DID method combines the strengths of the synthetic control method in constructing valid counterfactuals with the Difference-in-Differences approach, which accounts for temporal variations and unobserved heterogeneity, ensuring robust policy evaluation. The analysis of Beijing and Guangdong provides critical insights into the differential impacts of carbon trading policies, given their unique industrial and administrative structures.

As shown in Figure 1, the synthesized provinces provide a good pre-treatment fit for Guangdong Province but not for Beijing. To address this, the analysis employs a difference-in-differences (DID) approach for both regions, followed by a parallel trend test for Beijing to evaluate the comparability of pre-policy trends. The study first applies a difference-in-differences analysis to evaluate the policy's impact in both regions. Additionally, a parallel trend test is conducted for Beijing to verify whether pre-policy emission trends were comparable between Beijing and its synthetic counterpart. Passing the parallel trend test confirms the validity of the DID analysis, ensuring that the observed effects are attributable to the policy shock. The result of the difference-in-difference analysis can reflect the actual effects of policy shocks. The analysis results of Guangdong and Beijing are as follows:

The analysis results indicate that the coefficient of the interaction term is negative for both Beijing and Guangdong. For Beijing, the coefficient is significantly negative at the 0.01 level, suggesting a strong emission reduction effect. In contrast, the coefficient for Guangdong is

Table 2 Double difference analysis results of Beijing and Guangdong Province

	Beijing	Guangdong
	−0.538**	−0.030
	(−2.762)	(−0.206)
	−0.346**	−0.015
	(−3.553)	(−0.102)
	0.574***	0.530***
	(4.166)	(4.944)
_cons	4.484***	5.751***
	(65.117)	(53.792)
N	40.546	40.254
adj. R-sq	0	0

Note: t statistics in parentheses *p<0.05, **p<0.01, ***p<0.001

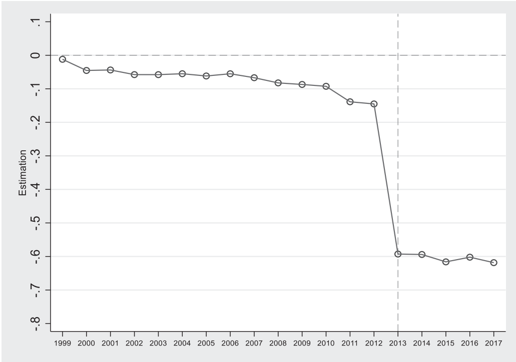

Fig. 7 Multi-period dynamic effects in Beijing

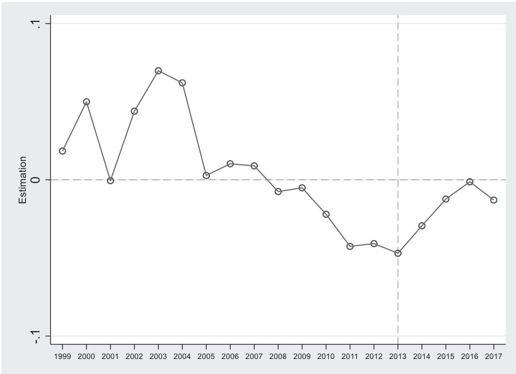

Fig. 8 Multi-period dynamic effects in Guangdong

negative but not statistically significant. At the same time, the parallel trend test for Beijing (Figure 7) shows that prior to the implementation of the pilot policy in 2013, the estimated emissions remained relatively stable. However, a significant reduction in emissions is observed post-2013, with levels remaining consistently low. This indicates that Beijing passed the parallel trend test, validating the DID analysis and confirming that the carbon trading pilot policy contributed to significant emission reductions. We can conclude that Beijing has passed the parallel trend test; that is, the analysis mentioned above is credible, and the carbon trading pilot policy has promoted Beijing's carbon dioxide emission reduction.

The multi-period dynamic effects analysis for Guangdong Province (Figure 8) reveals a noticeable emission reduction effect beginning in 2011, even before the formal implementation of the pilot policy. However, the magnitude of the negative effect diminishes after 2014, reaching its lowest point in 2016. Guangdong Province has made initial progress in optimizing its industrial structure, with shifts in the proportions of the primary, secondary, and tertiary sectors in its GDP. From the industry perspective's internal structure, the Guangdong production industry level is still low; significantly, the modern service industry lags behind producer services development, the proportion is still small high-tech manufacturing (Guangdong Academy of Social Sciences, 2017). In eastern and western Guangdong, the deployment of large-scale steel and petrochemical projects since 2013 has increased the presence of pollution-intensive industries. This expansion has exacerbated the regional environmental load, hindering effective reductions in carbon dioxide emissions.

5. Results and policy recommendations

5.1 Results

This study uses a synthetic control analysis based on annual panel data from 1998 to 2017 to evaluate the carbon trading pilot policies' effects on carbon dioxide emissions in Chinese provinces. The key findings are as follows:

(1) Effectiveness of carbon trading varies by region: The carbon trading policies demonstrated clear emission reduction effects in four pilot regions, including Chongqing. These regions showed substantial progress in reducing carbon dioxide emissions because of the policy interventions. However, in Guangdong Province, the synthesis performance in the early stages of the pilot implementation was poor, making it challenging to comprehensively evaluate and analyze the effectiveness of emission reduction efforts. Throughout the analysis period, Guangdong failed to exhibit significant emission reduction effects, highlighting the limitations of the policy's impact in this region.

(2) Contrasting results between Beijing and Guangdong: A deeper analysis using the double difference method revealed contrasting results between Beijing and Guangdong. In Beijing, the carbon trading policy significantly reduced emissions, with the cross-multiplication term showing statistical significance at the 0.01 level. Additionally, Beijing passed the parallel trend test, affirming the robustness of its emission reduction effects. This finding underscores the effectiveness of the carbon trading policy in Beijing, where policy implementation and pre-policy comparability aligned well. In contrast, Guangdong's cross-multiplication term was negative but not statistically significant. This suggests that while there may have been some reduction in emissions, the impact of the carbon trading policy in Guangdong was not as strong or consistent as in Beijing.

(3) Barriers in industrial transition: The industrial structure in Guangdong Province poses significant challenges to achieving meaningful emission reductions. The province has made initial progress in optimizing its industrial structure, transitioning towards a "three-two-one" pattern where the tertiary sector is growing in importance. However, the internal structure remains underdeveloped, with the modern service sector, particularly producer services, lagging behind. The proportion of high-tech manufacturing in Guangdong's economy remains small, limiting its ability to transition towards less carbon-intensive industries. Since 2013, eastern and western Guangdong have witnessed

the intensive deployment of pollution-intensive industries, such as large steel and petrochemical projects. Instead of reducing the environmental burden, this expansion has increased the regional environmental load, hindering effective carbon dioxide emission reductions.

5.2 Policy recommendations

This study underscores the value of using synthetic control analysis, which reduces biases in selecting control areas and mitigates errors caused by individual differences among pilot regions. Based on the findings, the following targeted recommendations are proposed to strengthen carbon trading policies and promote sustainable emission reductions:

(1) Prioritize key regions for focused impact: Municipalities like Beijing, Tianjin, Shanghai, and Chongqing played a pivotal role in the pilot phase due to their administrative and economic significance. Heavy industrial provinces such as Hubei and Guangdong were integral for addressing high emissions, while Shenzhen capitalized on its openness to trade and advanced financial markets, fostering an effective carbon market integrated with securities trading.

(2) Adopt region-specific strategies: Recognizing the variations in industrial structures, economic development levels, and emission profiles across regions, policymakers should implement tailored strategies. This includes leveraging regional strengths while addressing unique challenges to maximize the effectiveness of carbon trading policies.

(3) Expand the national carbon market through phased trials: A gradual approach, starting with the power industry, will allow policymakers to accumulate experience before extending carbon trading policies to other industries and regions. This step-by-step expansion ensures smooth integration and policy effectiveness.

(4) Accelerate structural reforms in high-emission regions: In provinces like Guangdong, where pollution-intensive industries dominate, transitioning away from these sectors is essential. Emphasis should be placed on developing modern service industries and high-tech manufacturing, particularly in eastern and western Guangdong, to optimize the industrial structure and achieve sustainable reductions.

(5) Integrate financial markets to enhance carbon trading efficiency: Leveraging Shenzhen's advanced financial market can increase trading activity and liquidity. Establishing strong connections between carbon markets and securities trading platforms will further improve market efficiency and transparency.

(6) Maintain a long-term perspective for carbon neutrality: To meet China's 2060 carbon neutrality goals, carbon trading policies should be gradually expanded and continuously refined. A long-term vision will ensure the achievement of domestic emission targets while contributing significantly to global climate goals.

These recommendations aim to create a more robust, equitable, and effective carbon trading framework, balancing regional priorities with national climate commitments.

5.3 Conclusion

The findings of this study underscore the need for a targeted and phased approach to carbon trading policy implementation. While regions like Beijing demonstrated strong policy effects, challenges in Guangdong Province highlight the importance of aligning industrial structure reforms with emission reduction strategies. By leveraging regional strengths, tailoring policies, and promoting phased market expansion, China can optimize its carbon trading system and contribute meaningfully to global climate goals.

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