Received: 26 March 2023 | Revised: 27 April 2023 | Accepted: 10 May 2023 | Published online: 15 May 2023

RESEARCH ARTICLE

Green and Low-Carbon Economy
2024, Vol. 2(2) 87–96
DOI: 10.47852/bonviewGLCE3202905

BON VIEW PUBLISHING

Does the Carbon Emissions Trading Scheme Improve Carbon Total Factor Productivity? Evidence from Chinese Cities

Wantong Yang[1] and **Ning Zhang**[1,*]

[1] *Institute of Blue and Green Development, Shandong University, China*

Abstract: Improving carbon total factor productivity (CTFP) is required for China's sustainable development, and the carbon emission trading scheme (ETS) is crucial to achieving this goal. In this paper, we calculate the city CTFP using meta Malmquist-Luenberger (MML) index from 2008 to 2019 and decompose it into efficiency change (EC), best practice gap change (BPC) and technology gap change (TGC). Then we construct a staggered Difference-in-Difference (DID) strategy to investigate the impact of regional ETS pilot policy on city-level CTFP using city panel data from 2008 to 2019. The main results show that the ETS pilot policy can increase CTFP by 3.3% in ETS cities compared to non-ETS cities. Mechanism tests suggest that the growth in CTFP mainly results from an increase in efficiency change and best practice gap ratio. Moreover, we use the CTFP calculated from the Solow residual instead of the CTFP obtained from the meta Malmquist–Luenberger index. We also perform other robustness tests to exclude the interference of potential threats to the results.

Keywords: ETS pilot policy, carbon total factor productivity (CTFP), staggered DID, meta Malmquist–Luenberger index

1. Introduction

A carbon emission trading scheme (ETS) is regarded as an effective means of environmental regulation to restrict global greenhouse gas emissions and combat climate change, which has received wide attention from governments and researchers. Chinese government formally proposed the establishment of ETS in the 12th Five-Year Plan (2011). The domestic ETS covering seven regional pilot areas in Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen has been trading since 2013, and ETS was also launched in Fujian in 2016. After that, a national carbon emission trading market was trading online in the power sector in July 2021. The ETS pilot policy is a key step toward China's ambitious emissions reduction targets, but the effectiveness of the policy is unknown in practice, giving us the motivation to explore the effect of ETS on carbon total factor productivity (CTFP).

Although many studies of ETS on efficiency and productivity exist, the majority of the literature uses data envelopment analysis (DEA) such as the Input Distance Function (IDF) model (Alem, 2023), Slacks Based Measure Data Envelopment Analysis (SBM-DEA) model (Wu et al., 2021a), Non-radial Directional Distance Function (NDDF) model (Yang et al., 2021), and Olley-Pakes (OP) and Levinsohn Petrin (LP) method (Chen et al., 2021). These methods can incorporate good and bad outputs into the model, adjust slack to avoid overestimating efficiency, address the radial problem that inputs and outputs vary in the same proportion, and account for intermediate inputs, but cannot tackle the problem of inter-group heterogeneity. Since differences in technology exist widely among samples, using the same technology benchmark can lead to distorted productivity measures. Oh (2010) proposed a meta frontier to solve this problem, following him this paper uses the meta Malmquist–Luenberger (MML) index to denote TFP. In terms of research content, the impact of the ETS pilot policy on city-level green total factor productivity (GTFP) (Li et al., 2022a; Shao et al., 2023), the effect of ETS pilot policy on province-level green development efficiency, and green production performance have also been investigated (Yang et al., 2021; Zhu et al., 2020), but the effect of ETS pilot policy on city-level CTFP has not existed.

GTFP is concerned with reducing environmental pollution and resource waste, while CTFP emphasizes cutting carbon emission reduction and climate change. In the dual carbon context, we shift our research perspective to CTFP although GTFP is also of importance. Besides, city-level data are more detailed and exhaustive than province-level data, containing additional information. And micro data lead to more accurate results and more generalizable conclusions. Therefore, the paper mainly does three works using city-level data from 2008 to 2019. First, we measure the MML index at city level and adjust it to CTFP using 2008 as the base year. Second, we analyze the effect of the ETS pilot policy on city-level CTFP drawing a staggered DID model. Third, we decompose the MML index into efficiency change (EC) item, best practice gap ratio (BPC) item, and technology gap ratio change (TGC) item, and they are adjusted to the base year of 2008 using a consistent rectify method, which serves to probe the roots and driving factor of CTFP growth.

*__Corresponding author:__ Ning Zhang, Institute of Blue and Green Development, Shandong University, China. Email: zhangn@sdu.edu.cn

The remainder of this paper is organized as follows. The literature review is in Section 2. Section 3 shows the identification method and strategy used in this paper. In Section 4, the data sources and processing are presented. The main results are given in Section 5. Lastly, Section 6 posits the conclusion and discussion.

2. Literature Review

Achieving the carbon peak target has no impact on China's economy, but reaching the carbon neutrality target has a very large impact on the economy, to maintain economic neutrality, China needs to increase TFP by 0.56%–0.57% annually from 2020 to 2060 (Huang et al., 2022). As a vital market-based environmental regulation tool, the ETS has attracted increasing attention during the past few years. Many scholars have studied its effects on TFP from different research dimensions. At the macro level, research often contains regional (Fan et al., 2022; Li et al., 2022b), provincial (Li et al., 2022c; Wu et al., 2021b), city (Li et al., 2022a), and county levels (Hu et al., 2022). The medium level of analysis focuses on different sectors such as agriculture (Yu et al., 2022), industry (Chen & Hibiki, 2022), manufacturing (Zhou et al., 2022), and pulp and paper sectors (Lundgren et al., 2015). At the microscopic level, researchers concentrate on the firm level (Bai et al., 2023; Wu & Wang, 2022). However, these studies may reach slightly varying conclusions due to the differences in information and data accuracy embedded within each level of analysis.

Most of the literature demonstrates that ETS pilot policy significantly increases TFP, although the magnitude of this impact varies. For instance, Li et al. (2022a) believe ETS can increase city GTFP by 11.4%, but the effects may be limited to the short term. Other studies have shown that the ETS pilot policy can raise firm TFP by 14% and improve the industrial subsector by 8.5% (Xiao et al., 2021; Zhang et al., 2022a). Additionally, implementing an ETS pilot policy could enhance China's A-share firm by as much as 5 percentage points (Bai et al., 2023). Promoting technological progress, adjusting energy structure, improving energy efficiency, and optimizing resource allocation are confirmed to be the main channels through which ETS has a positive impact on TFP (Bai et al., 2023; Tang & Xu, 2023; Wang et al., 2021). Other literature illustrates that there are two additional channels through which ETS can affect TFP: by improving the status of researchers and by strengthening financial aggregation (Huang & Chen, 2022; Wu & Wang, 2022). However, a small branch of the literature suggests that ETS may not improve TFP but rather promote technological progress (Fan et al., 2017; Li et al., 2022c). Besides, Chen and Hibiki (2022) find no significant effect on industrial firm productivity from the ETS pilot policy.

Furthermore, several pieces of literature have focused on the price of carbon emissions. It is relatively low in China, which has led to inactive trading in the carbon market (Zhang et al., 2022b). However, a persistent and significant positive causal link has been found between the price of carbon emissions and firm TFP. Specifically, Chinese firm TFP could improve by approximately 22.73% if China's carbon emission price were equivalent to that of the EU (Wu & Wang, 2022). Similarly, Pan et al. (2022) and Lundgren et al. (2015) both underline that a high price of carbon emissions can enhance the impact of the ETS pilot policy on TFP. Additionally, the ETS pilot policy and SO_2 reduction efforts synergistically reduce emissions to achieve green development goals (Wu et al., 2021b).

In summary, the existing literature has provided valuable insights into our understanding of ETS. However, the effect of the regional ETS pilot policy on CTFP remains unclear at city level. Therefore, this paper focuses on answering this question by using the ETS as a quasi-experiment to explore their impact on city-level CTFP (adjusted by the MML index). We employ a string of robustness tests to check the stability and consistency of our main findings and also analyze the primary channels through which ETS has an impact.

3. Methodology

Based on the MML index by Oh (2010), we measure the CTFP of Chinese cities from 2008 to 2019 and perform multiplication decomposition of the MML index. Then, to study the impact of TES on city-level CTFP, we obtain CTFP by adjusting the MML index with 2008 as the base year. We assume that CTFP is equal to 1 in 2008 and calculate subsequent years' CTFP by multiplying its MML index with the previous year's CTFP. Finally, since trading is gradual, we employ a staggered DID strategy to estimate the ETS's effect on city-level CTFP.

3.1. The directional distance function

Following Chung et al. (1997), the directional distance function (DDF) is defined as:

$$\vec{D}\left(\boldsymbol{x},\boldsymbol{y},\boldsymbol{b};\vec{g}_y,\vec{g}_b\right) = max\left\{\beta : \left(\boldsymbol{x},\boldsymbol{y}+\beta\vec{g}_y,\boldsymbol{b}-\beta\vec{g}_b\right) \in P(x)\right\} \tag{1}$$

It is often referred to as a multi-objective optimization 'problem where the object is to maximize the desirable output (y) and simultaneously minimize the undesirable output (b). The direction vector $\vec{g} = \left(\vec{g}_y,\vec{g}_b\right)$ specifies the desirable output increase and the undesirable output decrease. The production possibility set, denoted as P, is defined as follows: $\mathrm{P(x)} = \{(\mathrm{x,y,b}) \mid x \text{ can produce } (\mathrm{y,b})\}$. P(x) satisfies the assumptions of weak disposability and null-jointness. The value of the DDF is represented by β.

3.2. The MML index

Due to the varying environmental production technologies across different groups, it is not appropriate to compare their efficiency and productivity directly. To address this inter-group heterogeneity, Oh (2010) proposed meta frontier and MML, which builds on the ML index. MML index can be defined as follows:

$$\mathrm{MML}(\mathrm{x}^t,\mathrm{y}^t,\mathrm{b}^t,\mathrm{x}^{t+1},\mathrm{y}^{t+1},\mathrm{b}^{t+1}) = \frac{1+\vec{D}^G(\mathrm{x}^t,\mathrm{y}^t,\mathrm{b}^t)}{1+\vec{D}^G(\mathrm{x}^{t+1},\mathrm{y}^{t+1},\mathrm{b}^{t+1})} \tag{2}$$

where $\vec{D}^G(\mathrm{x,y,b}) = \max\{\beta : (\mathrm{x},\mathrm{y}+\beta y,\mathrm{b}-\beta b) \in \mathrm{P}^G(\mathrm{x})\}$ represents the global DDF, and s = t,t+1 are defined on the global benchmark technology set $\mathrm{P}^G(\mathrm{X})$.

Moreover, the MML index can be broken down into three components to investigate the driving factors of productivity growth, which are detailed as follows:

$$
\begin{aligned}
&\mathrm{MML}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) \\
&= \frac{1+\vec{D}^G(x^t, y^t, b^t)}{1+\vec{D}^G(x^{t+1}, y^{t+1}, b^{t+1})} \\
&= \frac{1+\overrightarrow{D^t}(x^t, y^t, b^t)}{1+\vec{D}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \\
&\times \frac{\left(1+\vec{D}^I(x^t, y^t, b^t)\right)/\left(1+\vec{D}^t(x^t, y^t, b^t)\right)}{\left(1+\vec{D}^I(x^{t+1}, y^{t+1}, b^{t+1})\right)/\left(1+\vec{D}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})\right)} \\
&\times \frac{\left(1+\vec{D}^G(x^t, y^t, b^t)\right)/\left(1+\vec{D}^I(x^t, y^t, b^t)\right)}{\left(1+\vec{D}^G(x^{t+1}, y^{t+1}, b^{t+1})\right)/\left(1+\vec{D}^I(x^{t+1}, y^{t+1}, b^{t+1})\right)} \\
&= \frac{TE^{t+1}}{TE^t} \times \frac{BPR^{t+1}}{BPR^t} \times \frac{TGR^{t+1}}{TGR^t} \\
&= EC \times BPC \times TGC
\end{aligned} \tag{3}
$$

The above equation involves three crucial benchmark technologies: contemporaneous benchmark technology, intertemporal benchmark technology, and global benchmark technology. The contemporaneous DDF, denoted as $\vec{D}^s(x, y, b) = \max\{\beta : (x, y+\beta y, b-\beta b) \in P^s\}$, is defined based on the contemporaneous technology of a specific group for $s = t, t+1$. The intertemporal DDF, represented by $\vec{D}^I(x, y, b) = \max\{\beta : (x, y+\beta y, b-\beta b) \in P^I\}$, is defined based on the intertemporal technology of a specific group. Finally, the global DDF, denoted as $\vec{D}^G(x, y, b) = \max\{\beta : (x, y+\beta y, b-\beta b) \in P^G\}$, is defined based on the global technology of the full decision-making unit (DMU).

The MML index is broken down into three components, namely EC, BPC, and TGC. EC represents the ratio of technical efficiency from period t to t + 1, which measures the movement of DMU toward the contemporaneous technology frontier in period t + 1 compared to period t. If EC > 1 (or < 1), it indicates an improvement (or loss) in efficiency. BPC is the best practice gap ratio term that quantifies the variation in the best practice gap from period t to t + 1. It shows how much closer or farther away the contemporaneous technology frontier is relative to a specific group's intertemporal technology frontier. BPC > 1(or < 1) implies that the distance between the technology frontier and the specific group's intertemporal technology frontier is getting closer (or farther) in period t + 1 relative to period t. TGC, the technology gap ratio change term, corresponds to a specific group's intertemporal technology frontier catching up the global technology frontier. TGC > 1 (or < 1) means the technology gap between intertemporal technology frontier and global technology frontier is decreasing (or increasing) by a given group. In Figure 1, EC, BPC, and TGC of group1 can be denoted as $\frac{o1b1}{o2b2}$ for EC, $\frac{o1c1/o1b1}{o2c2/o2b2}$ for BPC, and $\frac{o1d1/o1c1}{o2d2/o2c2}$ for TGC.

To evaluate the contribution of the three drivers of CTFP growth, the contribution rate of EC, BPC, and TGC is calculated in our analysis, which satisfies $EC^{t,t+1}_{contri} + BPC^{t,t+1}_{contri} + TGC^{t,t+1}_{contir} = 1$. The formula is as follows:

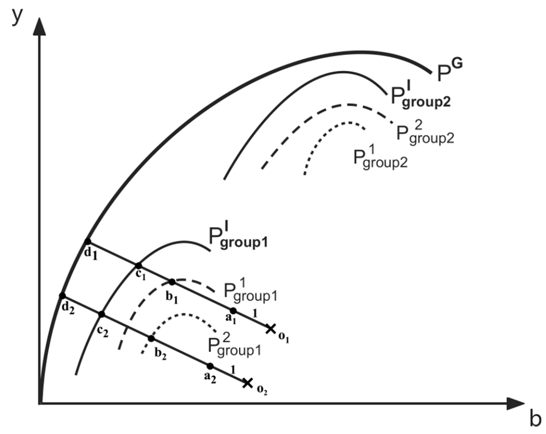
$$EC_{contri}{}^{t,t+1} = \frac{EC^{t,t+1}}{EC^{t,t+1} + BPC^{t,t+1} + TGC^{t,t+1}} \tag{4}$$

$$BPC_{contri}{}^{t,t+1} = \frac{BPC^{t,t+1}}{EC^{t,t+1} + BPC^{t,t+1} + TGC^{t,t+1}} \tag{5}$$

$$TGC_{contri}{}^{t,t+1} = \frac{TGC^{t,t+1}}{EC^{t,t+1} + BPC^{t,t+1} + TGC^{t,t+1}} \tag{6}$$

where they represent the contribution rates of different driving factors to CTFP growth from period t to t + 1.

Figure 1
Graphical representation of MML index



Notes: The thick solid line P^G represents the global technology frontier, while the solid line P^I represents intertemporal technology frontiers of specific groups 1 and 2. The dashed lines draw contemporaneous technology frontiers. The subscript of P denotes different groups, and the superscript represents different periods. o1a1 and o2a2 describe the direction vector

3.3. A staggered DID for CTFP

ETS officially began trading in Beijing, Tianjin, Shanghai, Shenzhen, and Guangdong in 2013, followed by Hubei and Chongqing in 2014. Staggered DID is an effective approach for addressing the contemporaneous trend of confounding factors that may exist when evaluating policies implemented year by year. This approach provides an ideal setting for accessing the impact of TES on CTFP. For city i, province j in region r at year t, following Cui et al. (2021) the formula is given:

$$
\begin{aligned}
CTFP_{ijrt} = \alpha + \beta_1 \mathrm{DID\_trading}_{\,ijrt} + \beta_2 \mathrm{DID\_announcement}_{\,ijrt} \\
+ \eta_i + \gamma_t + \varepsilon_{it}
\end{aligned} \tag{7}
$$

where the dependent variable is the CTFP of city i year t. $\mathrm{DID\_trading}_{\,ijrt}$ is a binary variable that equals one if city i implements ETS trading at year t and zero otherwise. $\mathrm{DID\_announcement}_{\,ijrt}$ equals to one if city i year t (2011 or 2012) announces it as an ETS pilot policy and zero otherwise. η_i, γ_t, and ε_{it} refer to the city fixed effects, year fixed effects, and random disturbance term, respectively. β_1 is the parameter of interest that captures the trading effect and represents the average effect of the ETS pilot policy on CTFP. β_2 captures the announcement effect.

To ensure the staggered DID model is an unbiased estimator, it is essential to verify that treated group and control group exist similar trends before the implementation of policy, which can ensure that any difference observed between the groups after policy implementation can be attributed to the policy itself rather than the pre-existing difference in trends between the groups. Namely, the parallel trend hypothesis should be satisfied. Therefore, we adopt event study method, which contains 6 years before and after the TES transaction, and the estimated formula is as follows:

$$TFP_{it} = \alpha_0 + \sum_{-6}^{6} \alpha_k \times D_{i,t_0+k} + \eta_i + \gamma_t + \varepsilon_{it} \tag{8}$$

where subscript t_0 is the year that ETS is trading, and k is the relative time of the ETS trading year. D_{i,t_0+k} is a collection of dummy variables corresponding to the year in which ETS is trading. η_i, γ_t, and ε_{it} refer to the city fixed effects, year fixed effects, and random disturbance term, respectively.

4. Data

To calculate the MML index, we employ labor (L), capital stock (K), and energy consumption (E) as inputs, GDP (Y) as desired output, and carbon dioxide emissions (C) as undesired output. We use two databases to obtain these city data from 2008 to 2019.

The data utilized in this study are sourced from the China City Statistical Yearbook, except for CO_2 emissions data which are obtained from the CEADs database. The number of employed people is utilized as a labor indicator. Due to the lack of official data, we utilize the perpetual inventory method to estimate the capital stock. Real capital stock and real GDP are measured using a constant price of 2000 to eliminate inflation effects. Energy consumption is calculated by summing up natural gas, liquefied petroleum gas, and electricity consumption (converted to standard coal). Table 1 presents the summary statistics of these variables for the period spanning 2008 to 2019.

5. Empirical Results

5.1. DEA result

Productivity improvement has three scenarios, the first involves efficiency catching up of the sample to the contemporaneous technology frontier. The second is technological progress narrows down the contemporaneous technology frontier toward a specific group's intertemporal technology frontier. The last one is the movement of the intertemporal technology frontier toward the global technology frontier, which is the enhancement of the technology leadership effect of a specific group. To explore the main driving factors of CTFP for both ETS and non-ETS groups, we computed the contribution rates of EC, BPC, and TGC for every group in different periods. As displayed in Table 2, the sum of these contribution rates is equal to one.

From 2008 to 2012, the TES group experienced CTFP growth mainly due to technology progress (BPC). Then, the catch-up effect (EC) and technology progress interlace became the most dominant driving factor. Compared to the ETS group, TGC has a more substantial role in driving CTFP growth for non-ETS group, suggesting that technology leadership is more commonly present

Table 1
Descriptive statistics of inputs and outputs used to calculate MML (2008–2019)

Variable	Unit	Obs.	Mean	Std. dev.	Min	Max
Panel A: Treated group						
Capital stock (K)	10^9 RMB	298	978.2	1368	62.03	7242
Labor (L)	10^4 Num.	298	146.1	208.1	11.96	986.9
Energy (E)	10^4 Tce	298	511.8	822.1	7.181	4067
Real GDP (Y)	10^9 RMB	298	427.8	566.8	30.22	2708
CO_2 emissions (C)	10^6 Tons	298	48.56	51.81	4.148	207.6
Panel B. Control group						
Capital stock (K)	10^9 RMB	1,431	581.8	563.0	23.22	3907
Labor (L)	10^4 Num.	1,431	58.37	58.87	4.210	649.3
Energy (E)	10^4 Tce	1,431	167.2	182.6	5.596	1477
Real GDP (Y)	10^9 RMB	1,431	188.2	188.3	6.398	1492
CO_2 emissions (C)	10^6 Tons	1,431	46.62	47.09	1.342	457.8

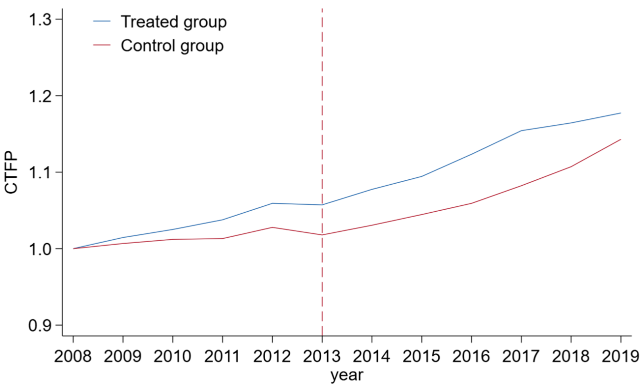
Notes: This table presents the descriptive statistics of both treatment and control samples. Panel A displays the characteristics of treated group, and panel B reports the characteristics of control group.

Table 2
The contribution of EC, BPC, and TGC to the growth of CTFP (2008–2019)

Period	08–09	09–10	10–11	11–12	12–13	13–14	14–15	15–16	16–17	17–18	18–19
Panel A: ETS group											
EC	0.328	0.328	0.332	0.325	0.348	0.344	0.333	0.335	0.403	0.326	0.348
BPC	0.342	0.342	0.342	0.343	0.325	0.328	0.343	0.339	0.275	0.346	0.323
TGC	0.330	0.330	0.326	0.332	0.327	0.328	0.324	0.326	0.322	0.328	0.329
Source	BPC	BPC	BPC	BPC	EC	EC	BPC	BPC	EC	BPC	EC
Panel B: Non-ETS group											
EC	0.330	0.325	0.343	0.321	0.332	0.331	0.33	0.326	0.339	0.325	0.326
BPC	0.323	0.334	0.321	0.34	0.329	0.33	0.332	0.337	0.327	0.344	0.341
TGC	0.347	0.342	0.336	0.339	0.339	0.339	0.338	0.337	0.334	0.332	0.333
Source	TGC	TGC	EC	BPC	TGC	TGC	TGC	BPC	EC	BPC	BPC

Notes: This table lists the contribution rates of EC, PBC, and TGC to CTFP growth respectively, which sum up to 1. Panel A shows the outcomes of the ETS group, and panel B shows the outcomes of the non-ETS group.

Figure 2
The mean value of carbon total factor productivity (CTFP) in treated group and control group per year



Notes: The CTFP of ETS cities is denoted by the blue line, while the red line represents the CTFP of non-ETS cities. The vertical line indicates when most ETS began trading (2013)

in non-ETS group. This situation may arise because ETS group is subject to greater constraints by carbon emissions regulations. As a result, element allocation can become distorted and technological innovation became more challenging for them.

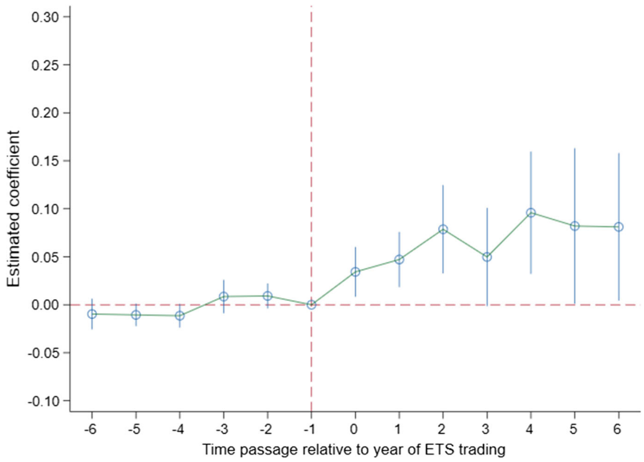
Figure 2 demonstrates the mean values of CTFP in different groups per year. It can be observed that after the ETS trading, CTFP in the treated group is higher than that of the control group. Moreover, this trend continues to increase within 4 years of ETS trading. This roughly indicates that the ETS pilot policy has a potentially positive effect on raising city-level CTFP. Therefore, it is required to conduct statistical analysis to determine if the gap is due to the ETS trading and if it is significant statistically.

5.2. The effect of ETS pilots on CTFP

This paper explores the impact of the ETS pilot policy on city-level CTFP using the staggered DID estimator from 2008 to 2019. To detect whether there are any notable distinctions between the treated group and control group before the ETS trading, we implement an event study by using the year before the ETS trading as our base year. Figure 3 displays the estimated coefficients along with their corresponding 95% confidence intervals. We discover that all coefficients are insignificant before treatment, but become significant after treatment, which means that our staggered DID estimator is unbiased and the estimation results are plausible.

The outcomes of the baseline model are displayed in Table 3. The first column uses fixed effects for province and year, with clustering at province level. In column (2), we use tighter city fixed effects in place of province fixed effects. In the third column, we cluster at province-by-year level as a baseline model while controlling for city and year time-invariant characteristics using city fixed effects and year fixed effects. Across all models, a statistically insignificant announcement effect suggests that the declaration of ETS in 2011 does not have an impact on CTFP, and the expectation effect is not present. Moreover, the trading effect is significant at 1% level, suggesting ETS trading has increased CTFP effectively. The coefficient is 0.033, implying that the gap in CTFP between the treated and control groups increased by 3.3% before and after the onset of the ETS policy.

Figure 3
Test for parallel trend



Notes: The point estimates are represented by hollow points, and the 95% confidence intervals are indicated by the vertical lines. The model uses city fixed effects and year fixed effects, with standard errors clustered at province-by-year level

The multi-period DID estimate is essentially a weighted average of multiple single-period DID estimates. To avoid estimation bias due to bad controls, we perform Goodman–Bacon decomposition (Goodman-Bacon, 2021). As shown in Table 4 and Figure 4, the weight of bad control Later T vs. Earlier C is only 0.5%, which is very small and can be seen as our main finding is unbiased.

5.3. Robustness tests

The subsection performs a series of auxiliary tests that aim to demonstrate the validity and stability of the baseline results and exclude any potential threats. The main results are presented in Table 5. Specifically, column (1) in Table 5 represents the baseline model, which is the same as that shown in Table 3.

First, to deal with any interference caused by unobservable time-invariant characteristics, we utilize region-by-year fixed effects as an alternative for both city and year fixed effects. The use of region-by-year fixed effects is particularly relevant in the context of China, where there exists a significant gap in regional development. As presented in column (2), the results remain similar to our main findings.

Second, more rigid clustering may result in insignificant regression results. To address any within-group autocorrelation present in the panel data, we replace province-by-year cluster with city-by-year cluster. As shown in column (3), the trading effects remain significant at 1% level and the announcement effect is not significant. These findings suggest that our findings are robust even when different clustering methods are employed.

Third, we recognize that bootstrap is an important interval estimation technique in non-parametric statistics. To define standard errors, we employ 2000 times bootstrap method. As shown in column (4), our results remain consistent with our baseline findings.

Fourth, as a validity check, we impose a placebo test by setting the wrong trading year. In column (5), we shift the trading time forward by 1 year (i.e., 2012 or 2013) to examine whether there is the trading effect. As expected, the coefficient turned out to be insignificant, thus further supporting our primary finding.

Table 3
The DID estimates the results of the carbon emissions trading scheme (ETS) on city-level CTFP

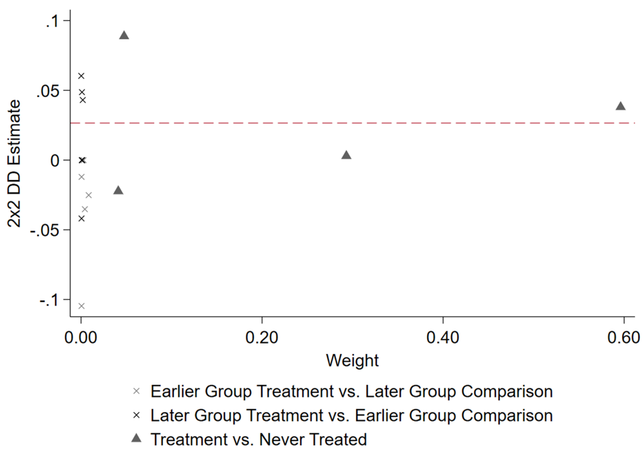
	(1) Alternative fixed effects	(2) Alternative clustering	(3) Baseline
DID_trading	0.049***	0.033**	0.033***
	(0.017)	(0.015)	(0.010)
DID_announcement	0.018	0.019	0.019
	(0.012)	(0.013)	(0.011)
_cons	1.039***	1.040***	1.040***
	(0.001)	(0.001)	(0.002)
Province FE	YES	NO	NO
City FE	NO	YES	YES
Year FE	YES	YES	YES
Cluster	Province	Province	Province-by-year
N	1729	1729	1729
Adjusted R^2	0.212	0.565	0.565

Notes: The dependent variable is the city-level CTFP. Each column is a separate DID estimator. DID_trading presents the dummy variable of whether trade and DID_announcement present the dummy variable of whether announcement. Column (1) employs fixed effects for province and year, with clustered standard errors at province level. Column (2) substitutes city fixed effects for province fixed effects. Column (3) serves as the baseline model and incorporates fixed effects for both city and year, with clustered standard errors at province-by-year level. The standard errors are reported in parentheses. ** denotes significance at the 0.05 level, and *** indicates significance at the 0.01 level.

Table 4
Goodman–Bacon decomposition weights and coefficients

DD Comparison	Weight	Avg. DD Est
Earlier T vs. Later C	0.017	−0.023
Later T vs. Earlier C	0.005	0.022
T vs. Never treated	0.978	0.027

Figure 4
Goodman–Bacon decomposition



Fifth, to mitigate the impact of measurement errors, we substitute the dependent variable using the TFP calculated by the Solow residual approach. Following reestimation using Equation (7), the magnitude and significance of the trading effect in column (6) remain largely unchanged. It confirms the validity of our identification strategy.

Finally, the extreme values in the sample can have a dramatic effect on the results. To address this issue, we trim the top and bottom 5% tails of the CTFP data. The outcomes are shown in column (7) and are not far from the baseline results. All the above checks illustrate that our baseline results are robust and plausible.

The results from our previous baseline regressions and a set of robustness tests illustrate that regional ETS pilot policy can increase city CTFP significantly. On this basis, identifying the potential mechanisms behind the impact is needed. To do so, we explore the impact mechanisms of ETS trading on CTFP with three decomposition terms of the MML index.

The primary results are presented in Table 6, where fixed effects and clustering are consistent with those in the baseline model. Columns (1)–(3) show the effect of ETS trading on CTFP through EC, BPC, and TGC, respectively. As shown in column (1), ETS trading can significantly improve efficiency, showing that efficiency catch-up is a critical pathway that starts to emerge after trading. In column (2), it is noticeable that the ETS pilot policy increases CTFP by improving the BPC. Technology advancement is an influential channel from the ETS announcement. This suggests that cities have been moving toward the intertemporal technology frontier and improving low-carbon techniques to cope with impending carbon regulation since the ETS pilot policy was announced. Column (3) reveals that the ETS pilot policy reduces the TGC, probably due to the constraints imposed by the carbon regulation causing the leading technology to degrade and fail in performing optimal factor allocation under free market conditions.

5.4. Placebo test

To verify that the staggered DID estimator is unbiased, we perform a placebo test. Specifically, we randomly assign ETS to different cities to generate a false treated group, while the remaining cities are used as the control group. Then we build the staggered DID estimator using these false treated variables and time variables interacting. The simulation that the random assignment and estimation process are repeated 2000 times and the distribution of estimated coefficients from all 2000 simulations

Table 5
Robustness test results of staggered DID models

	(1) Baseline	(2) Alternative fixed effects	(3) Alternative clustering	(4) Alternative standard errors	(5) Placebo test	(6) Alternative TFP	(7) Exclude outliers
DID_ trading	0.033***	0.059***	0.033***	0.033***	0.021	0.044***	0.037***
	(0.010)	(0.009)	(0.008)	(0.009)	(0.011)	(0.014)	(0.008)
DID_announcement	0.019	0.019**	0.019	0.019	0.009	0.025	0.009
	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.016)	(0.008)
_cons	1.040***	1.038***	1.040***	1.040***	1.045***	0.740***	1.037***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)
City FE	YES	NO	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	YES	YES	YES	YES
Region-by-year FE	NO	YES	NO	NO	NO	NO	NO
Cluster	Province-by-year	Province-by-year	City-by-year		Province-by-year	Province-by-year	Province-by-year
N	1729	1729	1729	1729	1557	1729	1729
Adjusted R^2	0.565	0.141	0.565	0.565	0.609	0.918	0.633

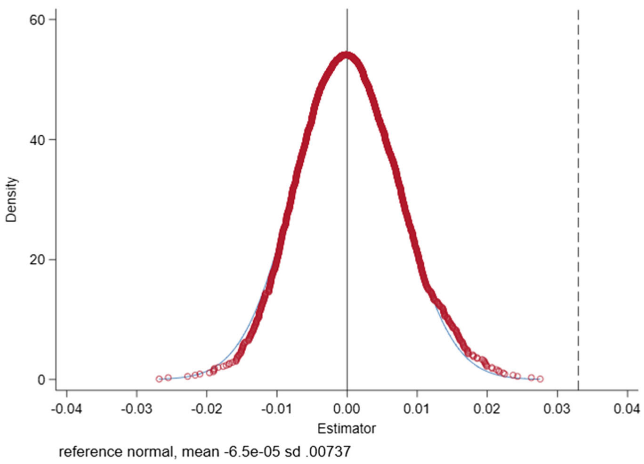
Notes: The dependent variable is the CTFP of city level. Each column is a separate DID estimator. Column (1) represents the baseline model. Column (2) includes region-by-year fixed effects, where "region" pertains to the eastern, central, and western regions geographically. In column (3), both city fixed effects and year fixed effects are used, clustered standard errors at city-by-year level. Column (4) uses the bootstrap standard errors; we implement bootstrap 2000 times. A placebo test is listed in column (5), assuming the ETS announcement and trading time delay of 1 year compared to the real policy time. Column (6) changes the calculation method of TFP, using the Solow residual. Column (7) winsorizes the top and bottom 5% of samples. The standard errors are in parentheses. ** denotes significance at the 0.05 level, and *** indicates significance at the 0.01 level.

Table 6
The DID estimates the results of ETS on EC and BPC, TGC

	(1) EC	(2) BPC	(3) TGC
DID_ trading	0.151***	0.049**	−0.170***
	(0.025)	(0.023)	(0.020)
DID_announcement	−0.021	0.084***	−0.052**
	(0.016)	(0.022)	(0.021)
_cons	0.968***	0.979***	1.113***
	(0.003)	(0.003)	(0.003)
City FE	YES	YES	YES
Year FE	YES	YES	YES
Cluster	Province-by-year	Province-by-year	Province-by-year
N	1729	1729	1729
Adjusted R^2	0.528	0.508	0.809

Notes: The dependent variable is the EC, BPC, and TGC of city level. Each column is a separate DID estimator. All models use city fixed effects and year fixed effects, while standard errors are clustered at province-by-year level. The standard errors are in parentheses. ** denotes significance at the 0.05 level, and *** indicates significance at the 0.01 level.

Figure 5
The Kernel density of estimates in the placebo test



Notes: The probability distribution of estimated coefficients is shown, which are obtained from 2000 randomized simulations where ETS is assigned to the samples, and the dashed vertical line represents the baseline result

is plotted in Figures 4 and 5. The regression estimated coefficients are normally distributed and symmetrically distributed around zero, which further supports our main findings.

6. Discussion

ETS is widely acknowledged as an economically efficient tool for reducing emissions, and more and more countries and regions are using ETS as a means of combating climate change. Since 2013, China has been executing a regional ETS pilot policy across some provinces and cities. This paper aims to answer the question of whether the regional ETS pilot policy is effective in improving CTFP at city level. In this paper, we regard the regional ETS as a quasi-experiment to study the effect of ETS pilot policy on city CTFP. We use city panel data from 2008 to 2019 and employ a staggered DID model to conduct our analysis. The following are the primary findings drawn from our research.

Firstly, the ETS pilot policy demonstrates a significant trading effect, but no announcement effect is observed. Following the implementation of ETS trading, cities that adopt ETS show a 3.3% improvement in CTFP compared to cities that do not implement ETS. This result is in line with previous studies that have shown ETS can reduce emissions at a lower cost and increase TFP. Secondly, our study also shed light on the factors contributing most to CTFP growth in different groups over time. We find the growth in CTFP in cities that adopted ETS is primarily driven by EC or BPC. Interestingly, the growth in CTFP in cities without ETS is sometimes driven by TGC, this implies that leading technology appears in non-ETS cities. Thirdly, efficiency catch-up is a positive channel that starts with ETS trading, while technological progress is a positive one that starts with ETS announcement. However, leading technology is a negative one.

Overall, our findings indicate that regional ETS pilot policy in China has been effective in improving CTFP at city level. This has important implications for the design and operation of the national carbon emission trading market. To successfully achieve the dual carbon goals, expanding the national carbon emission trading market to include other sectors is a necessary step. During this process, it is important to consider the order and pace of expansion, and the experiences and lessons learned from the regional ETS pilot in various sectors can serve as valuable references.

In addition, some limitations to our study should be noted. As we mentioned in introduction, the regional ETS pilot in China is implemented in three phases. However, due to the lack of data, our sample in this study does not include data after the implementation of the policy in Fujian province (after 2016). This means that our study only covers the first two ETS pilots, and the results may not capture the impact of ETS in Fujian province. Further research should include data from all three phases to provide a more comprehensive assessment in the future. Another limitation is that we only focus on the impact of ETS on CTFP and do not consider other environmental or economic outcomes (Cui et al., 2021). Moreover, we do not take into account the potential spillover effects of the ETS pilot policy on neighboring cities. Carbon constraints imposed by ETS may cause firms to relocate to neighboring cities that are not subject to ETS policy, which could potentially lead to carbon spillover and weaken policy effects. Therefore, the findings of our paper should be viewed with caution.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

Ning Zhang is the Editor-in-Chief for *Green and Low-Carbon Economy*, and was not involved in the editorial review or the decision to publish this article. The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

References

Alem, H. (2023). The role of green total factor productivity to farm-level performance: Evidence from Norwegian dairy farms. *Agricultural and Food Economics*, *11*(1), 2. https://doi.org/10.1186/s40100-023-00243-0.

Bai, C., Liu, H., Zhang, R., & Feng, C. (2023). Blessing or curse? Market-driven environmental regulation and enterprises' total factor productivity: Evidence from China's carbon market pilots. *Energy Economics*, *117*, 106432. https://doi.org/10.1016/j.eneco.2022.106432.

Chen, G., & Hibiki, A. (2022). Can the carbon emission trading scheme influence industrial green production in China? *Sustainability*, *14*(23), 15829. https://doi.org/10.3390/su142315829.

Chen, H., Guo, W., Feng, X., Wei, W., Liu, H., Feng, Y., & Gong, W. (2021). The impact of low-carbon city pilot policy on the total factor productivity of listed enterprises in China. *Resources, Conservation and Recycling*, *169*, 105457. https://doi.org/10.1016/j.resconrec.2021.105457.

Chung, Y., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management*, *51*(3), 229–240. https://doi.org/10.1006/jema.1997.0146.

Cui, J., Wang, C., Zhang, J., & Zheng, Y. (2021). The effectiveness of China's regional carbon market pilots in reducing firm emissions. *Proceedings of the National Academy of Sciences*, *118*(52), e2109912118. https://doi.org/10.1073/pnas.2109912118.

Fan, D., Fu, J., & Wang, W. (2022). How does carbon emission trading influence firm's total factor productivity. *Systems Engineering – Theory & Practice*, *42*(3), 591–603. https://doi.org/10.12011/SETP2021-1298.

Fan, D., Wang, W., & Liang, P. (2017). Analysis of the performance of carbon emissions trading right in China-The evaluation based on the difference-in-difference model. *China Environmental Science*, *37*(6), 2383–2392.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014.

Hu, Y., Liu, J., & Ahmed, M. (2022). Does emission trading policy restrain economy? A county-scale empirical assessment from Zhejiang Province of China. *Energy Policy*, *168*, 113138. https://doi.org/10.1016/j.enpol.2022.113138.

Huang, D., & Chen, G. (2022). Can the carbon emissions trading system improve the green total factor productivity of the pilot cities?—A spatial difference-in-differences econometric analysis in China. *International Journal of Environmental Research and Public Health*, *19*(3), 1209. https://doi.org/10.3390/ijerph19031209.

Huang, S., Du, C., Jin, X., Zhang, D., Wen, S., Wang, Y., . . . , & Jia, Z. (2022). The boundary of porter hypothesis: The energy and economic impact of China's carbon neutrality target in 2060. *Energies*, *15*(23), 9162. https://doi.org/10.3390/en15239162.

Li, C., Qi, Y., Liu, S., & Wang, X. (2022a). Do carbon ETS pilots improve cities' green total factor productivity? Evidence from a quasi-natural experiment in China. *Energy Economics*, *108*, 105931. https://doi.org/10.1016/j.eneco.2022.105931.

Li, J., Huang, D., & Wu, X. (2022b). The Impact of China's carbon emission trading policy on green total factor productivity – Influence analysis based on super-EBM and multiple mediators. *Polish Journal of Environmental Studies*, *31*(6), 5107–5123. https://doi.org/10.15244/pjoes/151538.

Li, X., Shu, Y., & Jin, X. (2022c). Environmental regulation, carbon emissions and green total factor productivity: A case study of China. *Environment, Development and Sustainability*, *24*(2), 2577–2597.https://doi.org/10.1007/s10668-021-01546-2.

Lundgren, T., Marklund, P., Samakovlis, E., & Zhou, W. (2015). Carbon prices and incentives for technological development. *Journal of Environmental Management*, *150*, 393–403. https://doi.org/10.1016/j.jenvman.2014.12.015.

Oh, D. (2010). A metafrontier approach for measuring an environmentally sensitive productivity growth index. *Energy Economics*, *32*(1), 146–157. https://doi.org/10.1016/j.eneco.2009.07.006.

Pan, X., Pu, C., Yuan, S., & Xu, H. (2022). Effect of Chinese pilots carbon emission trading scheme on enterprises' total factor productivity: The moderating role of government participation and carbon trading market efficiency. *Journal of Environmental Management*, *316*, 115228. https://doi.org/10.1016/j.jenvman.2022.115228.

Shao, W., Yang, K., & Jin, Z. (2023). How the carbon emissions trading system affects green total factor productivity? A quasi-natural experiment from 281 Chinese cities. *Frontiers in Energy Research*, *10*, 895539. https://doi.org/10.3389/fenrg.2022.895539.

Tang, A., & Xu, N. (2023). The impact of environmental regulation on urban green efficiency—Evidence from carbon pilot. *Sustainability*, *15*(2), 1136. https://doi.org/10.3390/su15021136.

Wang, S., Chen, G., & Han, X. (2021). An analysis of the impact of the emissions trading system on the green total factor productivity based on the spatial difference-in-differences approach: The case of China. *International Journal of Environmental Research and Public Health*, *18*(17), 9040. https://doi.org/10.3390/ijerph18179040.

Wu, G., Hong, J., Tian, Z., Zeng, Z., & Sun, C. (2021a). Assessing the total factor performance of wastewater treatment in China: A city-level analysis. *Science of the Total Environment*, *758*, 143324. https://doi.org/10.1016/j.scitotenv.2020.143324.

Wu, Q., Tambunlertchai, K., & Pornchaiwiseskul, P. (2021b). Examining the impact and influencing channels of carbon emission trading pilot markets in China. *Sustainability*, *13*(10), 5664. https://doi.org/10.3390/su13105664.

Wu, Q., & Wang, Y. (2022). How does carbon emission price stimulate enterprises' total factor productivity? Insights from China's emission trading scheme pilots. *Energy Economics*, *109*, 105990. https://doi.org/10.1016/j.eneco.2022.105990.

Xiao, J., Li, G., Zhu, B., Xie, L., Hu, Y., & Huang, J. (2021). Evaluating the impact of carbon emissions trading scheme on Chinese firms' total factor productivity. *Journal of Cleaner Production*, *306*, 127104. https://doi.org/10.1016/j.jclepro.2021.127104.

Yang, L., Li, Y., & Liu, H. (2021). Did carbon trade improve green production performance? Evidence from China. *Energy Economics*, *96*, 105185. https://doi.org/10.1016/j.eneco.2021.105185.

Yu, Z., Mao, S., & Lin, Q. (2022). Has China's carbon emissions trading pilot policy improved agricultural green total factor productivity? *Agriculture*, *12*(9), 1444. https://doi.org/10.3390/agriculture12091444.

Zhang, H., Liu, Y., Choi, Y., Yang, L., & Li, X. (2022a). Has China's pilot emission trading system promoted technological progress in industrial subsectors? *Environmental Research Letters*, *17*(11), 115007. https://doi.org/10.1088/1748-9326/ac9e0c.

Zhang, N., Zhao, Y., & Wang, N. (2022b). Is China's energy policy effective for power plants? Evidence from the 12th Five-Year Plan energy saving targets. *Energy Economics*, *112*, 106143. https://doi.org/10.1016/j.eneco.2022.106143.

Zhou, Z., Ma, Z., & Lin, X. (2022). Carbon emissions trading policy and green transformation of China's manufacturing industry: Mechanism assessment and policy implications. *Frontiers in Environmental Science*, *10*, 984612. https://doi.org/10.3389/fenvs.2022.984612.

Zhu, B., Zhang, M., Huang, L., Wang, P., Su, B., & Wei, Y. (2020). Exploring the effect of carbon trading mechanism on China's green development efficiency: A novel integrated approach. *Energy Economics*, *85*, 104601. https://doi.org/10.1016/j.eneco.2019.104601.

How to Cite: Yang, W., & Zhang, N. (2024). Does the Carbon Emissions Trading Scheme Improve Carbon Total Factor Productivity? Evidence from Chinese Cities. *Green and Low-Carbon Economy*, *2*(2), 87–96. https://doi.org/10.47852/bonviewGLCE3202905