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Kaifeng Wang
Guangdong Academy of Social Sciences
Yunmin Zeng
Guangdong Academy of Social Sciences
Yonghua Luo
Guangdong University of Petrochemical Technology
Yanliang Zhu
jxzyl@gdupt.edu.cn

Guangdong University of Petrochemical Technology

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Effect of higher NO_x emissions tax rates on carbon efficiency: Quasi-natural experiment based on China's NO_x emissions tax rate reform

Kaifeng Wang [a], Yunmin Zeng [a], Yonghua Luo [b], Yanliang Zhu [b*]

[a] Institute for Environment and Development, Guangdong Academy of Social Sciences, Guangzhou, China

[b] School of Economics and Management, Guangdong University of Petrochemical Technology, Maoming, China

***Corresponding author: Prof. Yanliang Zhu, Ph. D.**

E-mail: jxzyl@gdupt.edu.cn (Yanliang Zhu)

ORCid: 0000-0002-3071-056X (Yanliang Zhu)

Abstract: This study employs a quasi-natural experiment with a difference-in-differences (DID) approach to estimate the impact of China's nitrous oxide (NO_x) emissions tax reform on carbon efficiency (CE), defining the reform as the adoption of rates above the national minimum to precisely capture regional heterogeneity. Results reveal that the NO_x emissions tax rate reform significantly accelerates sample cities' CE progress and has beneficial spatial spillover effects, driving CE improvement in surrounding areas. The reform exhibits more pronounced CE enhancement effects in eastern China and cities with a larger share of secondary industry. Furthermore, the reform effectively synergizes with policy measures such as clean energy promotion, air pollution prevention and control plans, and the Low-Carbon City pilot policy, yielding more positive outcomes. The NO_x emissions tax rate reform enhances CE through promoting green technological innovation and curbing industrial agglomeration in pilot regions. Furthermore, synergistic NO_x and carbon dioxide (CO_2) reduction is the most comprehensive and primary channel for promoting CE progress through NO_x emissions tax rate reform. The findings reveal the ancillary influence of NO_x emissions tax on CO_2 reduction and their potential as an interim instrument before China enacts a

carbon tax, offering a practical, efficiency-aligned mitigation pathway.

Keywords: Difference-in-differences; nitrous oxide (NO_x) emissions; Taxes; carbon dioxide (CO_2) emissions; Carbon efficiency

1. Introduction

China is the world's largest industrial producer, energy consumer, and carbon dioxide (CO_2) emitter, while also being severely affected by air pollution. Numerous studies have demonstrated that pursuing shared benefits in controlling different types of emissions is an effective approach to simultaneously address CO_2 emissions and air pollution challenges (Leinert et al., 2013; Ye & An, 2017; Mortha et al., 2021). Moreover this is the primary reason that China proposed enhancing synergistic emissions reduction of CO_2 and air pollutants in its *14th Five-Year Plan* and the *Implementation Plan for Synergistic Pollution and Carbon Reduction*.

However, in China, environmental taxes are solely levied on pollutants, with a long-term lack of direct tax instruments to address substantial CO_2 reduction pressure. Therefore, it is essential to explore how better overall pollutant reduction (tax) policies can accelerate the CO_2 reduction process and achieve synergistic emissions reduction.

Among the major pollutants targeted by China's environmental tax, nitrous oxide (NO_x) has become the most emitted gaseous pollutant in China,[①] underscoring the NO_x emissions tax's importance in China's environmental tax system. Although NO_x includes the greenhouse gas (GHG) N_2O, in practice, China only monitors and taxes NO and NO_2 (following the HJ479-2009 national standard). Therefore, China's NO_x emissions tax is not a typical climate policy.

[①] According to the database of the National Bureau of Statistics of China (https://data.stats.gov.cn), annual NO_x emissions since 2017 have reached more than twice that of sulfur dioxide (SO_2), which is the second most emitted GHG pollutant in China.

Nevertheless, as illustrated in Fig. 1, NO_x and CO_2 emissions in China are highly homologous. Although China's NO_x emissions tax primarily targets producers and differs from other countries' energy use–based carbon taxes in many tax design features, we argue that taxing NO_x emissions would affect the shared sources of NO_x and CO_2 emissions. Therefore, ignoring the synergistic CO_2–NO_x reduction effects of NO_x emissions taxes may critically underestimate the policy's impact.

Therefore, this study adopts a quasi-natural experiment difference-in-differences (DID) approach to examine the impact of China's escalating NO_x emissions tax rates[①] on carbon efficiency (CE) progress to explore the role of China's NO_x emissions tax in mitigating global warming and subsequent policy implications.

[①] China transformed the 1982 pollutant discharge fee system into an environmental tax system in 2018 (Guo et al., 2019). To avoid confusion and misunderstanding, we reference Jiang et al. (2022) and collectively refer to China's pollutant discharge fees and environmental taxes on NO_x emissions as the NO_x emissions tax.

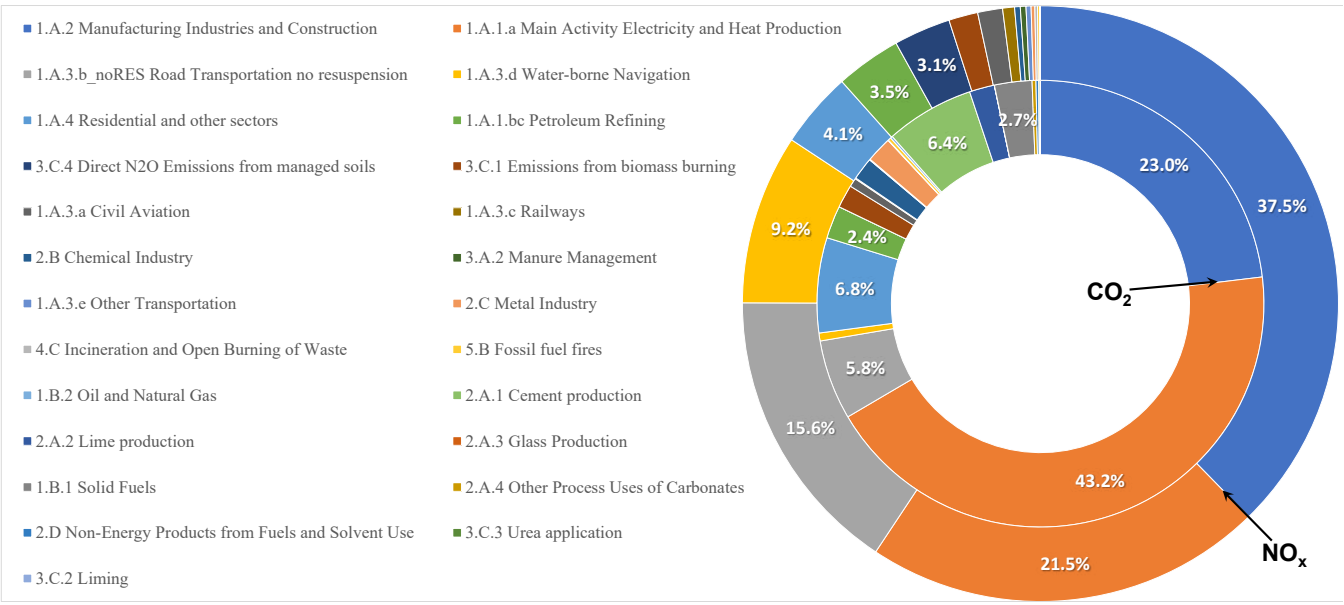


Fig. 1 Comparing the proportional structure of NO_x and CO_2 emissions sources

Note: The data in this figure are from the Emissions Database for Global Atmospheric Research (EDGAR) (https://edgar.jrc.ec.europa.eu), using emissions source classification standards that are consistent with the 2006 Intergovernmental Panel on Climate Change National Greenhouse Gas Inventories.

Numerous studies have analyzed the synergistic emissions reduction effects of tax policies on GHGs and pollutants. For example, through simulation, Leinert et al. (2013) found that Ireland's carbon tax reduced CO_2 emissions but unexpectedly increased NO_x emissions. Ye and An (2017) conducted a quasi-natural experiment revealing that a carbon tax significantly improved air quality in countries with high fine particulate matter ($PM_{2.5}$) concentrations. Through causality testing, Chien et al. (2021) demonstrated that environmental taxes in the United States can simultaneously suppress $PM_{2.5}$ pollution and CO_2 emissions. Mortha et al. (2021) confirmed that Japan's carbon tax policy can reduce emissions of atmospheric pollutants, including NO_x.

Current research has primarily focused on how carbon reduction policies affect atmospheric pollutant emissions, whereas studies exploring the reverse impact of atmospheric pollutant control policies on carbon emissions are limited. For instance, García-Gusano et al. (2015) used The Integrated MARKAL–EFOM System (TIMES) model, which considers GHGs and

atmospheric pollutants, to evaluate the effectiveness of SO_2 and NO_x emissions taxes in Spain. Xiao et al. (2021) used a dynamic stochastic general equilibrium model, revealing that positive policy synergies are evident between SO_2 emissions tax and carbon trading policies. Compared with research on SO_2 emissions tax, studies on NO_x emissions tax's carbon reduction effects are limited. Using a simulation approach, Jiang et al. (2022) determined that NO_x emissions tax can simultaneously reduce CO_2 and SO_2 emissions, emphasizing that NO_x emissions tax should be the core of tax-based synergistic emissions reduction strategies.

Relevant literature has engaged in a research trend using total emissions or emissions intensity as indicators to evaluate carbon reduction effectiveness (Rodriguez et al., 2020). However, evidence from studies such as Proskuryakova and Kovalev (2015) and Rodriguez et al. (2020) has revealed that emissions intensity only encompasses emissions and output metrics, which may introduce policy bias. Conversely, Guo and Jin (2025) demonstrated that total factor productivity (TFP) indicators based on distance functions provide a more precise reflection of production activities' input–output (IO) complexity, thus possessing superior policy guidance value. Studies by Iftikhar et al. (2018), Yu and Zhang (2021), and Chen and Wang (2022) have employed distance functions grounded in data envelopment analysis (DEA) to evaluate CE based on TFP, highlighting that such indicators integrate carbon emissions with economic IO efficiency, providing more policy-relevant insights for China's high-quality development strategy, which emphasizes efficiency improvements.

This research trend highlights the necessity of calculating efficiency indicators using DEA and distance functions to evaluate the effects of NO_x tax reform. Nevertheless, studies assessing the carbon reduction effects of the NOx emissions tax using a DEA efficiency framework remain limited.

To supplement existing research, this study builds a quasi-natural DID experimental framework, measuring the CE progress for 284 cities in the Chinese mainland using DEA and

evaluating the NO_x tax reform's contribution to CE. With no carbon tax in China, this analysis of synergistic emissions reduction and the NO_x tax's impact demonstrates its practical value as a transitional carbon reduction tool. This finding reveals the value of optimizing NO_x tax policy application and reform, offering key insights for China's future synergistic emissions reduction policies, highlighting the study's practical significance.

Compared with the extant literature, the main innovations and distinctive features of this study are twofold. First, contrary to theoretical simulation-based studies (García-Gusano et al. 2015; Albrizio et al., 2017; Jiang et al., 2022), this study uses CE to empirically evaluate China's NO_x emissions tax rate reform, confirming its synergistic NO_x–CO_2 reduction effect using mediating effect analysis. Although NO_x's share in China's GHG emissions has surged, exceeding twice that of SO_2 since 2017 (Crippa, 2024), it has received little attention in existing empirical studies. Therefore, this study provides urgently needed empirical evidence for optimizing NO_x reduction strategies and complements prior theoretical studies.

Second, this study pioneers a novel policy event definition and DID variable setting in NO_x emissions tax research. Previous quasi-natural experiments have used simple 0-1 DID variables based on the first post-2004 (or post-2018) tax hike (Guo et al., 2019; Liu et al., 2022), neglecting subsequent hikes. Moreover, most regions' tax rate hikes have jointly followed the central government's new minimum tax standards, and only a few have adopted rates above the legal minimum, altering regional disparities (see Fig. 2). Therefore, as a key improvement over previous studies' DID designs, such as Liu et al. (2022), this study's policy event represented by the DID variable is the sample regions' adoption of NO_x emissions tax rates above the national minimum (rather than the first rate hike). This enables us to more accurately determine whether relatively higher NO_x emissions tax rates can generate carbon emissions reduction policy effects.

The remainder of this study is structured as follows. Section 2 analyzes the theoretical

130 mechanism and proposes hypotheses, Section 3 introduces the methodology and data, Section
131 4 presents the results and discussion, and Section 5 presents the conclusions and policy
132 implications.

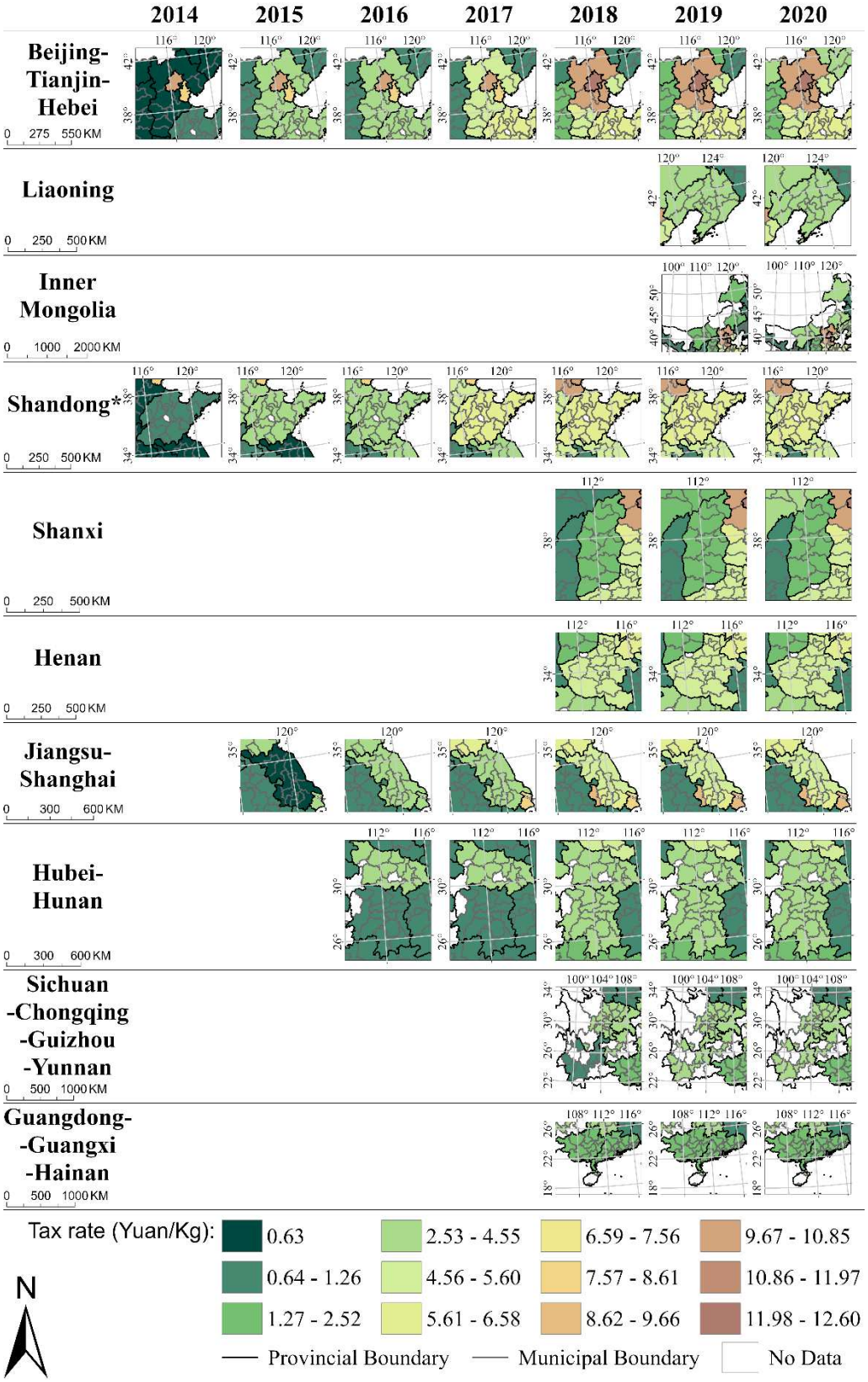


Fig. 2 NO_x emissions tax rates above the statutory minimum standard

Note: The data in this figure are sourced from the websites of 284 Chinese cities' environmental protection bureaus. *Due to space constraints, this figure represents the year each region initiated tax rates above statutory minimum standard, with the exception of Shandong province, which maintained the same elevated tax rate from 2008 to 2014.

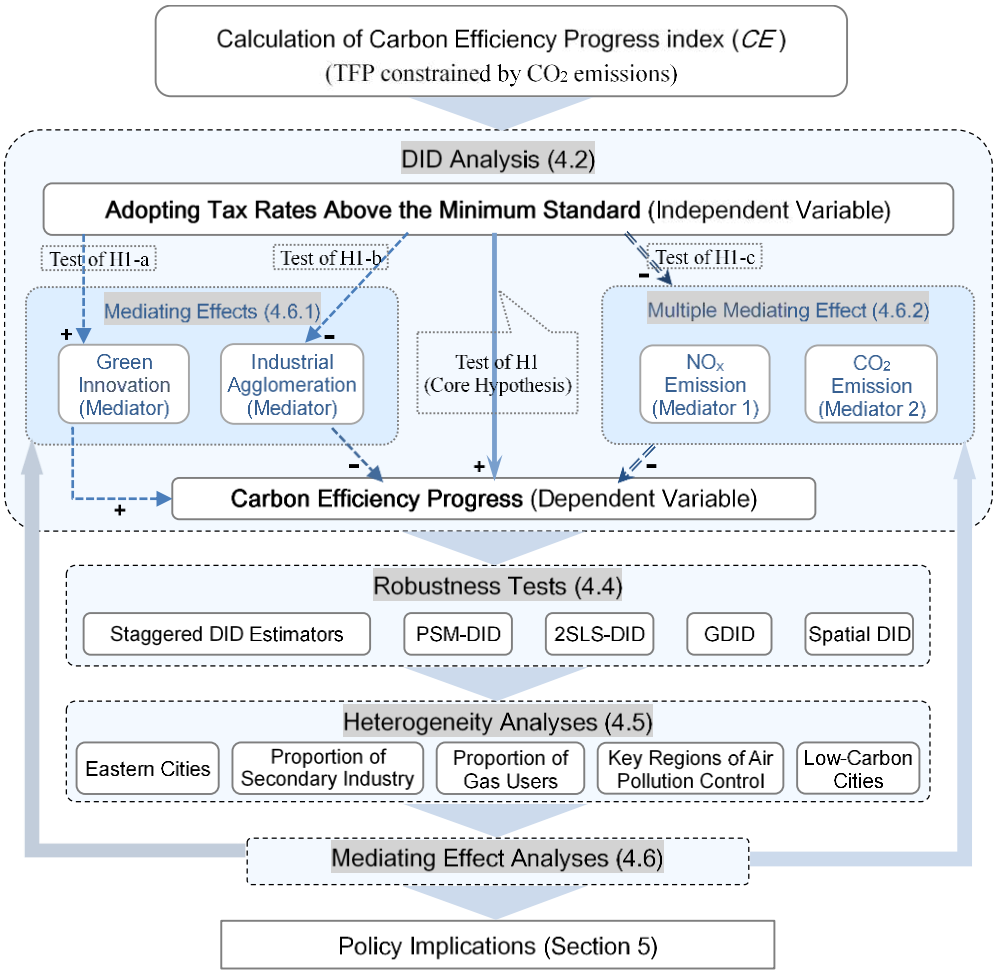


Fig. 3 Research framework.

2. Mechanisms and Hypotheses

2.1 CE Gains from NO_x Emissions Tax Reform

As illustrated in Fig. 1, approximately 60% of NO_x and CO_2 emissions originate from fossil fuels used in manufacturing, construction, electricity, and heating industries (IPCC 2006 codes 1.A.1.a and 1.A.2); therefore, taxing NO_x emissions can affect the shared sources of NO_x and CO_2 emissions.

China's NO_x emissions tax is an environmental regulation tool aligned with the Polluter Pays Principle, conveying clear and predictable price signals to emitters. Consequently, to reduce the tax burden, emitters facing higher NO_x emissions tax rates are more inclined to

achieve NO_x–CO_2 synergistic reduction and improve productivity through technological innovation and other paths (Albrizio et al., 2017; Iftikhar et al., 2018; Yu and Zhang, 2021; Jiang et al., 2022; Liu et al., 2022). Therefore, we propose the following core theoretical hypothesis (H1).

H1: NO_x emissions tax rate reform (adopting standards higher than the then-legal minimum) facilitates CE progress (TFP under CO_2 emissions constraints).

If H1 is confirmed, this study will examine the related mechanisms from the following three perspectives (see Fig. 2).

2.2 Mediating Effect of Green Innovation

Acemoglu et al. (2016) noted that economic incentive-based environmental regulations (e.g., subsidies and taxes) can promote research and development (R&D) resource transfer such as R&D funds and personnel to clean production areas, enabling emitters to advance long-term, endogenous green technological progress (Liu et al., 2022). This technological progress can accelerate CE progress through synergistic NO_x and CO_2 reduction and TFP improvement (Chien et al., 2021; Yu and Zhang, 2021). Therefore, this study proposes a theoretical mechanism hypothesis regarding the innovation effect (H1-a).

H1-a: NO_x emissions tax rate reform accelerates CE progress by promoting technological innovation.

2.3 Mediating Effect of Industrial Agglomeration

Beyond green innovation and cleaner production, stringent tax policies can curb carbon emissions and boost CE by altering high-emissions industries' local agglomeration (Agee et al.，2014；Xiao et al.，2021). Faced with tax pressure, high-emissions firms may downsize, exit, or relocate from high-tax regions (Cole et al., 2017; Yu and Zhang, 2021; Chen and Wang, 2022). These actions accelerate existing high-pollution industrial firms' relocation and deter new high-pollution industrial firms' entry or creation, resulting in lower output or fewer

174 firms (Zhang and Wang, 2014). Therefore, we propose the second mechanism hypothesis.

175 H1-b: NO_x emissions tax rate reform accelerates CE progress by inhibiting high-pollution
176 industrial firms' local agglomeration.

177 ***2.4 Mediating Effect of Synergistic Emissions Reduction***

178 As NO_x and CO_2 are often emitted into the atmosphere from the same source and through
179 the same process (fossil fuel use; see Fig. 1), control measures for NO_x emissions
180 simultaneously suppress CO_2 emissions, thereby reducing negative outputs in CE indicators
181 (Agee et al., 2014; Xiao et al., 2021; Jiang et al., 2022). The relevant physicochemical
182 mechanisms and process principles have been extensively studied in engineering and
183 technology fields (Day et al., 2005; Brattebø and Reenaas, 2012; Feng et al., 2018). Based on
184 these mechanisms, we propose the following hypothesis regarding the synergistic emissions
185 reduction effect (H1-c):

186 H1-c: NO_x emissions tax rate reform simultaneously suppresses NO_x and CO_2 emissions,
187 and the suppression of both types of emissions contributes to accelerating CE progress.

188 # 3. Methodology and Data

189 ***3.1 Carbon Efficiency (CE) Evaluation Method***

190 Among various DEA methods, this study adopts the Range Directional Model (RDM) to
191 calculate CE. The advantage of this approach is its invariance to the units of measurement and
192 shifts in the data under variable returns to scale (Portela and Thanassoulis, 2010). Using RDM
193 enables us to solve for sample cities' contemporaneous and global distance functions relative
194 to the optimal production frontier (Portela and Thanassoulis, 2010; Oh, 2010), with linear
195 programming solutions respectively denoted as $D_{i,t}^{*}$ and $D_{i,t}^{G*}$ (see Appendix A.5 for details).
196 Subsequently, we employ the Global Malmquist–Lüenberger (GML) index (Oh, 2010) to

197 calculate the intertemporal CE index ($CE_{i,t}^{t+1}$) as follows:

$$
\begin{aligned}
CE_{i,t}^{t+1} &= \frac{1+D_{i,t}^{G*}}{1+D_{i,t+1}^{G*}} \\
&= \left[\frac{1+D_{i,t}^{*}}{1+D_{i,t+1}^{*}}\right] \times \left[\frac{1+D_{i,t}^{G*}}{1+D_{i,t}^{*}} \times \frac{1+D_{i,t+1}^{*}}{1+D_{i,t+1}^{G*}}\right], \\
&= EC_{i,t}^{t+1} \times BPC_{i,t}^{t+1}
\end{aligned}
\tag{1}
$$

198

199 where subscript t denotes the year, and i and j are sequence numbers used to distinguish
200 different cities. $CE_{i,t}^{t+1}$ represents the CE index, reflecting the rate of CE progress (change
201 multiplier; for example, $CE_{i,t}^{t+1}$ = 1.03 indicates a 3% intertemporal increase in CE). The
202 efficiency progress index ($EC_{i,t}^{t+1}$) is generally considered a manifestation of management
203 efficiency improvement, whereas the technological progress index ($BPC_{i,t}^{t+1}$) reflects the
204 dynamic magnitude of technological advancement (Oh, 2010). In subsequent analyses, annual
205 CE indices are calculated as cumulative growth rates based on equation (1) (unless otherwise
206 specified), with the base year set as 2003 to accurately depict the trend of CE progress.

207 ***3.2 Quasi-Natural Experiment Method***

208 China's NO_x emissions tax rate adjustments are driven by administrative mandates from the
209 central government, constituting a suitable quasi-natural experiment. Referencing Beck et al.
210 (2010) and Yu and Zhang (2021), we employ the DID method to assess the impact of NO_x
211 emissions tax rate adjustments. The baseline DID model is calculated as follows:

212 $$CE_{i,2003}^{t} = cons + \alpha_1 TAXREF_{i,t} + X_{i,t}\beta + f_i + \mu_t + \varepsilon_{i,t}. \tag{2}$$

213 This equation is grounded in a multi-period panel data regression. The dependent variable
214 ($CE_{i,2003}^{t}$) represents the accumulated CE progress from 2003 measured by the GML index.

215 On the right-hand side of Equation (2), *TAXREF* is a binary DID variable (Beck et al.,
216 2010). α_1 is the coefficient of the DID variable, capturing the policy's average treatment effect.
217 *cons* denotes the constant term, $X_{i,t}$ is a k-dimensional row vector encompassing all control

variables, and β is a $k \times 1$ parameter vector for the control variables. f_i and μ_t respectively represent individual and time fixed effects (FEs). $\varepsilon_{i,t}$ is the independently and identically distributed random error term.

3.3 Data and Variable Selection

3.3.1 Data for CE Calculation

We classify the data used for measuring CE into input and output categories. Input data include energy and economic factor input subcategories. Energy input data are measured in 10,000 tons of standard coal, sourced from Yang et al. (2024), who based their series on provincial energy statistics from China's National Bureau of Statistics and disaggregated the verified provincial totals to prefecture-level cities using nighttime light data and socioeconomic factors. Economic factor input includes real fixed capital stock (measured in 100 million yuan), calculated using the perpetual inventory method (Jin et al., 2020), and total employment (measured in 10,000 persons), represented by the number of employees in urban firms.

Output indicators include carbon emissions and economic output subcategories. For carbon emissions, we use carbon emissions data from the Emissions Database for Global Atmospheric Research (EDGAR) (Crippa et al., 2024). The original data are in the form of geographical grids, with units of $Kg/m^2/s$. This study calculates the annual total carbon emissions flux (in Kg) for each sample city within city boundaries. The economic output indicator is cities' annual gross domestic product (GDP) in 10,000 yuan, which is deflated using the provincial Consumer Price Index (CPI), with 1992 as the base year.

Using these data, we employ MaxDEA software to calculate the CE based on the RDM method and GML index. As presented in Appendix Fig. A.1, the average CE index for all sample cities in 2022 is 1.17, indicating overall CE improvement in this period.

Considering DEA-based efficiency measures' sensitivity to techniques and data, this study

computes two additional CE indices. The first uses fossil fuel CO_2 data from the ODIAC database (http://www.odiac.org) instead of carbon emissions. The second adopts the Bounded Adjusted Measure (Cooper et al., 2011) over RDM. These indices are detailed in Appendix Fig. A.3. As illustrated in the figure, changes in data sources or methods only cause limited variations in CE trends, confirming the robustness of our measurement approach.

3.3.2 Difference-in-differences (DID) Model Variables and Data

(1) DID Variable Definition

Defining the policy event for the DID term is an innovation of this study. Since the NO_x emissions tax's introduction, the national minimum tax rate has progressively risen from 0.63 yuan/Kg to 1.26 yuan/Kg (a standard maintained after the transition from pollutant discharge fees to environmental taxes). Notably, although nearly all regions had raised NO_x emissions tax rates at least once by 2022, most have merely adhered to the escalating national minimum, maintaining tax rate convergence. Only a few cities adopting rates above the national minimum have widened regional tax rate disparities (see Fig. 1).

Therefore, this study classifies cities with NO_x emissions tax rates above the national minimum as the treatment group (others as control), setting *TAXREF* to 1 post-policy for treatment cities and 0 for controls. Treatment group selection and the determination of NO_x emissions tax rates are based on publicly released, legally binding provincial documents on environmental tax rates after 2003, which are rigorously enforced by prefecture-level and above cities within each province.

We contend that *TAXREF* better reflects regional tax rate disparities than initial hikes studied previously (e.g., Guo et al., 2019; Liu et al., 2022). Furthermore, unlike the comprehensive pilot policies such as the Low-Carbon City initiative with large and complex plans that vary by region, the policy event represented by the *TAXREF* DID variable is unambiguous due to the mandatory and statutory nature of taxation. Additionally, its regional

heterogeneity can be directly reflected by tax rate differences, facilitating the identification of policy effects.

(2) Control Variables

Referencing Dietz and Rosa (1997), we introduce per capita real GDP (*YCP*) and its quadratic term (deflated by provincial CPI with 1992 as the base year), urban population density (*POPUD*), and per capita scientific and technological financial expenditure (*RDEXP*) as control variables representing economic development, population aggregation, and technological level, respectively. Additional control variables include a traffic condition variable (Zhang and Wang, 2019) representing per capita road area (*ROAD*) and government oversight capacity and intensity, referring to the proportion of municipal public infrastructure investment (including investment in energy, environmental, and municipal cleaning fields) in fixed assets investment (*INVMPF*).

Table 1 presents the detailed descriptive statistics for all variable. Unless otherwise specified, all monetary data are deflated using the GDP deflators of the sample cities' respective provinces, with 2003 as the base year. To mitigate heteroskedasticity and scale disparities, we apply natural logarithm transformations to all data in DID models, except for the DID variable (*TAXREF*).

Table 1 Descriptive statistics.

	Variable	Obs	Mean Value	SD	Max	Min	Units
Explained variable	*CE*	5,396	1.101	0.279	0.319	4.111	-
Explanatory variable	*TAXREF*	5,396	0.239	0.427	0	1	-
	YCP	5,396	30,899.830	25,240.560	2,007.447	20,2446.8	Yuan / people
	POPUD	5,396	8,172.931	3,043.433	1,987.631	29,687.21	People / Km^2
Control variables	*RDEXP*	5,396	5,335.568	4,274.689	55.345	29,712.94	Yuan / people
	ROAD	5,396	18.883	10.647	2.280	123.548	m^2 / people
	INVMPF	5,396	2.782	4.172	0.0000992	93.699	%

3.4 Data Preprocessing

In addition to the DID variable and carbon emission-related data, data for other variables are sourced from *The Yearbook of China's Cities* or *The Yearbook of China's Urban Construction*. We screen and compile a panel dataset encompassing 284 prefecture-level and above cities from these yearbooks, spanning 2003–2022,[①] excluding other Chinese cities are due to severe data deficiencies.

4. Results and Discussions

4.1 Parallel Trend Test

Testing the parallel trend assumption is a crucial preliminary step to confirm DID applications. Referencing Beck et al. (2010), we use the following parallel trend test:

$$CE_{i,t} = cons + \sum_{k=1-p_b}^{9} \alpha_k T_{i,t}^{-k} + \sum_{s=1+p_b}^{9} \alpha_s T_{i,t}^{+s} + X_{i,t}\beta + f_i + \mu_t + \varepsilon_{i,t}, \quad (3)$$

where *pb* denotes the base period (relative to the actual policy implementation period). The two sets of vectors ($k \in \{1\text{-}p_b, 2\text{-}p_b, ..., -11, -12\}$) and ($s \in \{1+p_b, 2+p_b, ..., 11, 12\}$) represent years before and after policy implementation, respectively. Superscripts $-k$ ($+s$) indicate the amount of time relative to the policy event. Following Beck et al. (2010), we use the first period before the policy launch (−1 period) as the base period ($p_b = -1$). For example, if the policy reform in the *i*-th city was launched in 2009, and $t = 2009 - k$ (t = 2009+*s*), then $T_{i,t}^{-k}$ (or $T_{i,t}^{+s}$) equals 1; otherwise, $T_{i,t}^{-k}$ (or $T_{i,t}^{+s}$) equals 0.

As illustrated in Fig. 4, before the base period, the policy effect of $T_{i,t}^{-k}$ (i.e., α_k in Equation (3) does not significantly deviate from 0, indicating no policy effect. However, the $T_{i,t}^{+s}$ (i.e., α_s) policy effect becomes significantly greater than 0 after the base period. These

[①] The starting period of the data used for estimating the DID model is 2004, because the CE index based on DEA and GML equals 1 in the base year of 2003 and cannot be used in the regression.

results confirm that the parallel trend assumption holds, validating our DID framework.

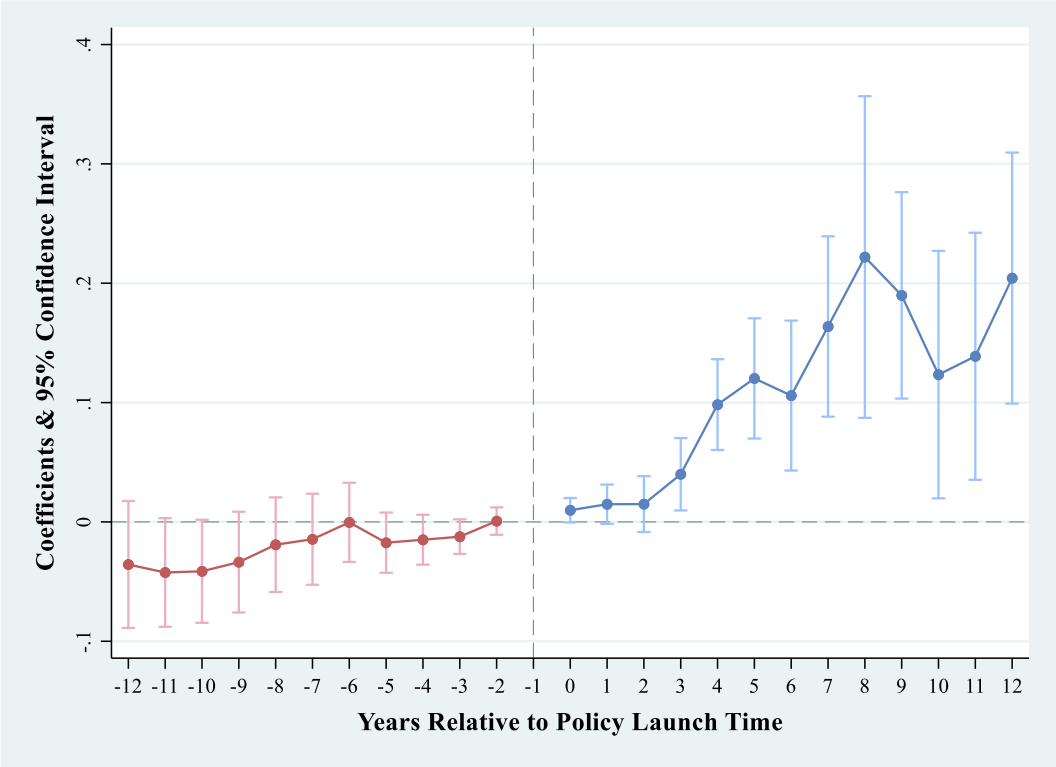


Fig. 4 Parallel trend test.

4.2 Benchmark Regression

Table 2 presents the baseline regression results of the baseline DID model (Model A) employing two-way fixed effects (TWFE). The parameter estimate for *TAXREF* is 0.0395 (p-value ≤ 0.01), indicating that cities in the sample experience a 3.95% increase in *CE* after adopting NO_x emissions tax rates higher than the national minimum standard (entering the treatment group). These findings confirm H1, highlighting the beneficial effects of the NO_x emissions tax rate reform on carbon emissions.

Table 2 Impact of NO_x emissions tax rate reform on carbon efficiency.

	Model A	**Model B**	**Model C**	**Model D**	**Model E**	**Model F**	**Model G**
	Benchmark Regression (TWFE)	Estimator from Borusyak et al. (2021)	PSM-DID	2SLS-DID (IV: *PRS* & *APDIST*)	GDID (Differences between tax rates and national standard)	Spatial-DID (SDM using spatial weight matrix)	Spatial-DID (SDM using economic distance spatial weights matrix)
Dep. Var.: / **Variables**	***CE***	***CE***	***CE***	***CE***	***CE***	***CE***	***CE***

	Model A	**Model B**	**Model C**	**Model D**	**Model E**	**Model F**	**Model G**
	Benchmark Regression (TWFE)	Estimator from Borusyak et al. (2021)	PSM-DID	2SLS-DID (IV: *PRS* & *APDIST*)	GDID (Differences between tax rates and national standard)	Spatial-DID (SDM using spatial weight matrix)	Spatial-DID (SDM using economic distance spatial weights matrix)
Dep. Var.: / **Variables**	***CE***	***CE***	***CE***	***CE***	***CE***	***CE***	***CE***
TAXREF	0.0395***	0.0614***	0.0349***	0.277***	-	0.026***	0.04***
	(0.0145)	(0.0133)	(0.00841)	(0.0665)	-	(0.0088)	(0.0067)
TAXREF × *NOTR*	-	-	-	-	0.0358***	-	-
	-	-	-	-	(0.0128)	-	-
W_s × *TAXREF*	-	-	-	-	-	0.0513*	-
	-	-	-	-	-	(0.0308)	-
W_s × *CE (Dependent Variable)*	-	-	-	-	-	0.761***	-
	-	-	-	-	-	(0.0308)	-
W_e × *TAXREF*	-	-	-	-	-	-	0.3544***
	-	-	-	-	-	-	(0.0907)
W_e × *CE (Dependent Variable)*	-	-	-	-	-	-	0.134*
	-	-	-	-	-	-	(0.0728)
Obs	5,396	5,396	3,819	5,396	5,396	5,396	5,396
Number of cities	284	284	201	284	284	284	284
R^2	0.173	-	0.190	0.034	0.175	0.8022	0.7913
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered at the city level are in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

4.3 Placebo Test

We conduct a placebo test to verify the reliability of the effect estimates from the DID model. Specifically, this involves randomly assigning hypothetical treatment groups and policy implementation years across the entire sample to generate fictitious DID variables, which are then subjected to regression analysis, performing 1,000 such tests to yield 1,000 fake treatment effect estimates. Fig. 5 presents the kernel density distribution of these placebo effects, revealing a significant divergence from the DID model's effect (indicated by the blue dashed line) that clusters 1,000 fake policy effects around zero. This confirms that our empirical results are not influenced by unobserved variables (Yu and Zhang, 2021) and instead provide a relatively accurate reflection of the true policy effect.

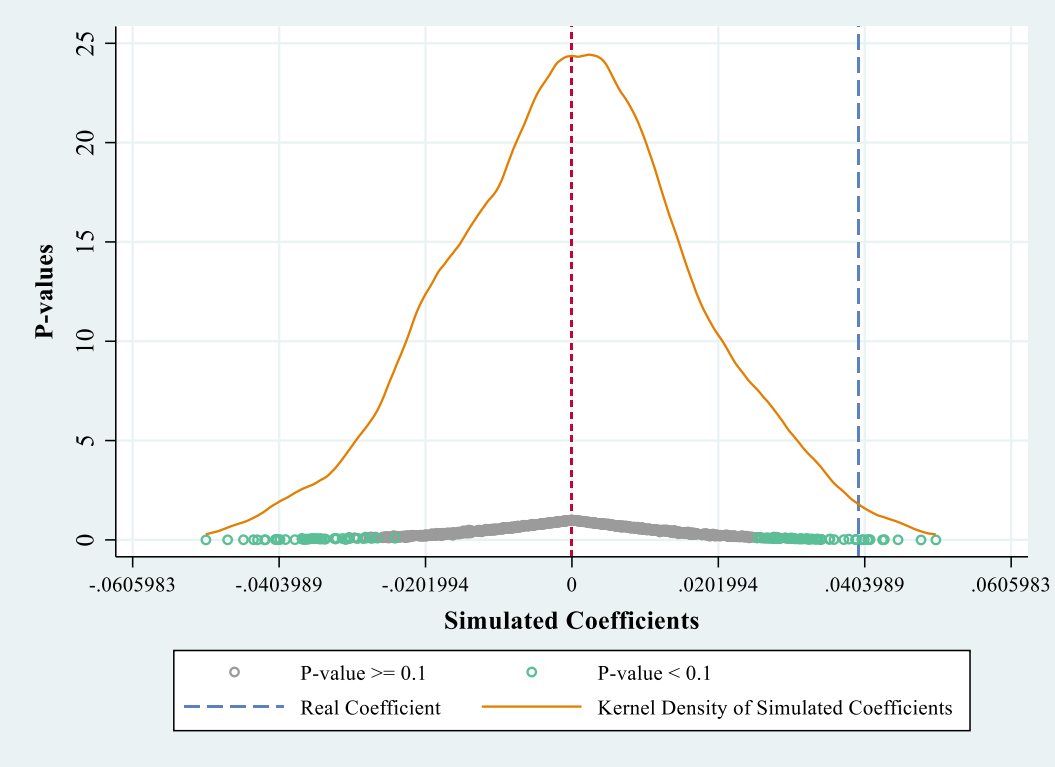


Fig. 5 Placebo test results.

4.4 Robustness Tests

In addition to robustness tests, the research in this subsection also aims to ascertain whether our conclusions are influenced by staggered DID, selection bias, and endogeneity, further validating the effectiveness of our empirical analysis.

4.4.1 Staggered DID Estimation

Considering that the NO_x emissions tax rate reform was implemented at different times across regions (see Fig. 2), our DID variable is staggered, which can cause DID TWFE analyses to potentially yield biased results (Borusyak et al., 2021). Therefore, we use the staggered DID estimators proposed by Borusyak et al. (2021) to re-examine the effect of NOx emissions tax rate reform. As presented in Table 2 (Models B and C), the point estimates produced by Borusyak estimator (0.0614, p-value $\leq$ 0.01) do not essentially differ from Model A, indicating that the staggered DID model does not compromise the accuracy of our primary conclusions.

346 *4.4.2 Propensity Score Matching*

347 Considering that the NO_x emissions tax rate reform defined in this study may not fully
348 satisfy the assumption of random assignment to the treatment group, we conduct annual
349 propensity score matching (PSM) on the panel data based on all control variables
350 (representing city characteristics) (Rosenbaum and Rubin, 1985; Yu and Zhang, 2021). The
351 comparison of standardized biases in Table 3 indicates that PSM significantly reduces the
352 characteristic differences between the treatment and control group samples.[①]

353 The regression results from the DID model using the PSM-DID data in Table 2 (Model C)
354 reveal an estimated policy effect of 0.0349 (p-value < 0.01), indicating that potential selection
355 bias does not fundamentally alter our baseline conclusions.

356 **Table 3 Mean standardized bias of variables before and after PSM.**

Bias (%) \ Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Unmatched	20.01	17.76	20.28	22.36	13.84	14.71	16.12	16.86	17.21	17.81	16.18	16.32	13.74	9.46	12.19	14.79	16.52	14.09	12.93
Matched	4.12	2.43	4.21	5.31	1.40	5.42	1.82	3.17	2.30	2.74	3.81	1.49	3.40	5.45	3.02	4.74	2.96	4.17	4.48

357 *4.4.3 Instrumental Variable Approach*

358 Considering the partial regional autonomy in adjusting NO_x emissions tax rates may
359 introduce endogeneity, we extend Model A using a DID-two-stage least squares (2SLS) model
360 (Model D), referencing Yu and Zhang (2021) and Chen and Wang (2022).

361 Following Fenske et al. (2023), we use two instrumental variables (IVs) in Model D. The
362 first is surface atmospheric pressure (*PRS*, in Pascals, sourced from the ERA5 database). This
363 variable is selected because plains and basins suitable for human settlement and industry in
364 China are primarily at low altitudes (Ma & He, 2021). Therefore, *PRS* has a theoretical
365 probability of positive correlation with *TAXREF* and strong exogeneity as a natural factor.

366 The second IV is *APDIST*, defined as the inverse of the shortest distance from a sample city

① Due to space limitations, only the mean standardization bias of all control variables is reported. The specific matching results (balance test results) of typical years (2004, 2011, and 2018) are presented in Appendix Tables A.3 and A.4.

to key air pollution control areas[①] (unit: per hundred kilometers to the negative first power). *APDIST* is theoretically likely to be positively associated with *TAXREF* because regional joint pollution control is highly valued in China. Geographic distance is purely natural, and the key areas are defined through China's top authorities' exogenous policy decisions (Fenske et al., 2023), so the exogeneity of *APDIST* has also been supported.

As seen in Table 2 and Appendix Table A.5,[②] the treatment effect estimates from Models E do not fundamentally differ from those of Model A, indicating that endogeneity does not significantly affect our DID model's validity.

4.4.4 Generalized DID

By multiplying *TAXREF* in Model A by the extent to which the tax rates exceed the national minimum standard (*NOTR*) (deflated using the provincial deflation index, with a base period of 2003), Model C can be extended to a generalized DID (GDID) model (Model E).

As observed in Table 2, the estimated policy effect based on Model E (0.332, p-value ≤ 0.01) is significantly positive, aligning with the direction of the effect from Model A (0.0395) but with a notably higher magnitude. This indicates that the 0-1 binary DID variable does not materially compromise the validity of our findings, although it overlooks cross-city differences in actual tax rates. Second, the higher estimated effects of Model E also indicate that higher tax rates can further improve treatment group cities' CE.

4.4.5 Spatial DID

We next extend Model A to the following spatial DID model (Models G and H), introducing spatial effects:

[①] Key regions vary by year and include the Two Control Zones for SO_2 and acid rain, as well as areas specified in national policies such as the Action Plan for Air Pollution Prevention and Control (September 2013), the Three-Year Action Plan for Winning the Blue-Sky Defense War (July 2018), and the Opinions on Deepening the Fight Against Pollution (November 2021).

[②] To save space, the full results of 2SLS model and its IV rationality test results are reported in Table A.5 in the supplementary materials.

$$CE_{i,t} = \rho_0 \sum_{j=1}^{n} W_{ij} CE_{j,t} + \alpha_1 TAXREF_{i,t} + \rho_1 \sum_{j=1}^{n} W_{ij}(TAXREF_{j,t}) + X_{i,t}\beta + \sum_{j=1}^{n} W_{ij} X_{j,t}\theta + f_i + \mu_t + \varepsilon_{i,t} \quad (4)$$

Equation (4) is grounded in the spatial Durbin model (SDM), where $\sum_{j=1}^{n} W_{ij}(CE_{i,t})$ denotes the spatial lagged dependent variable, $\sum_{j=1}^{n} W_{ij}(TAXREF_{j,t})$ represents the spatial lagged DID variable, and $\sum_{j=1}^{n} W_{ij} X_{j,t}$ signifies the spatial lags of all control variables. n is the total number of sampled cities (284), and W_{ij} is the element in the i-th row and j-th column of the spatial weight matrix. To further confirm robustness, we use a spatial weight matrix (W_s) and an economic distance spatial weight matrix (W_e) in Models G and H, respectively, which are defined as follows:

$$W_{s,ij} = \begin{cases} 1/d_{ij}, i \neq j \\ 0, i = j \end{cases}$$

$$W_{e,ij} = \begin{cases} W_{s,ij} \times \dfrac{1}{ypc_i - ypc_j}, i \neq j \\ 0, i = j \end{cases}, \quad (5)$$

$$i = 1, 2..., n$$

$$j = 1, 2..., n$$

where d_{ij} represents the circular distance between cities i and j (in hundreds of kilometers), and $ypc_i - ypc_j$ is the difference in per capita real GDP between cities i and j.

We employ the methods from Elhorst (2012) to regress Equation (4). As shown in Table 2 (Models G and H),[①] the coefficients of $W_s \times CE$ and $W_e \times CE$ are significantly positive but less than 1, indicating spatial autocorrelation in CE progress. The coefficients of $W_s \times TAXREF$ and $W_e \times TAXREF$ are both significantly positive, indicating that the tax reform

[①] To save space, the results of the direct effect (local impact) and indirect effect (spatial spillover) from the spatial econometric analysis are presented in Appendix Table A.7.

exhibits beneficial spatial spillover effects that may be attributable to spillover of green technology and environmental tournaments among city managers (H Hu and Zong, 2022; Chen and Wang, 2022). The estimated policy effects of the two spatial DID models (0.026 and 0.04, p-value < 0.01) are still close to Model A after using different weight matrices, indicating that spatial effects do not fundamentally affect our benchmark conclusions.

4.5 Heterogeneity Analyses

Referencing Yu and Zhang (2021), we further augment Model A by incorporating interactive terms between heterogeneous city variables and *TAXREF* to isolate the influence of regional characteristics and potential interference from other policies.

This study uses two categories of heterogeneous variables. The first includes regional characteristics, encompassing the dummy variable *EAST*, indicating China's geographical differences, and *SIND*, reflecting economic structural disparities based on the proportion of secondary industry in GDP. The second category comprises environmental governance and policy. The variable *GASR* represents the ratio of gas users to the total population to measure clean energy promotion, the dummy variable *APCTRL* denotes key regions under national pollution control plans for comprehensive atmospheric pollution management emphasizing NO_x emissions control, and the carbon reduction policy indicator *LCC* dummy variable is an indicator for Low-Carbon Cities pilot regions.

Table 4 Heterogeneity analysis.

	Model A	**Model H**	**Model I**	**Model J**	**Model K**	**Model L**
	Benchmark Regression (TWFE)	Eastern China	Proportion of secondary industry in GDP	Proportion of gas users in the population	Key regions in National Air Pollution Control Plans	Low-Carbon Cities
Dep. Var. / **Variables**	***CE***	***CE***	***CE***	***CE***	***CE***	***CE***
TAXREF	0.0395***	0.0206	0.0467***	0.0133	0.0210	0.0271*
	(0.0145)	(0.0147)	(0.0139)	(0.0145)	(0.0151)	(0.0143)
TAXREF × *EAST*	-	0.104***	-	-	-	-
	-	(0.0239)	-	-	-	-

	Model A	Model H	Model I	Model J	Model K	Model L
	Benchmark Regression (TWFE)	Eastern China	Proportion of secondary industry in GDP	Proportion of gas users in the population	Key regions in National Air Pollution Control Plans	Low-Carbon Cities
Dep. Var. / Variables	*CE*	*CE*	*CE*	*CE*	*CE*	*CE*
TAXREF × *SIND*	-	-	0.00279*	-	-	-
	-	-	(0.00151)	-	-	-
TAXREF × *GASR*	-	-	-	0.112***	-	-
	-	-	-	(0.0171)	-	-
TAXREF × *APCTRL*	-	-	-	-	0.0957***	-
	-	-	-	-	(0.0241)	-
TAXREF × *LCC*	-	-	-	-	-	0.137***
	-	-	-	-	-	(0.0308)
Obs	5,396	5,396	5,396	5,396	5,396	5,396
Number of cities	284	284	284	284	284	284
R^2	0.173	0.191	0.177	0.217	0.185	0.191

Note: Robust standard errors clustered at the city level are in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

The heterogeneity analysis results in Models H–L of Table 4 reveal a notably positive coefficient for the *TAXREF* × *EAST* interaction term, indicating that the reform significantly enhanced CE in eastern China. The coefficient for the *TAXREF* × *SIND* interaction term is positive but only significant at the 10% level, indicating stronger CE improvement in regions with higher industrial and construction sector shares, consistent with China's environmental tax predominantly targeting the industrial sector, although its actual efficacy remains subject to enhancement. The coefficients for *TAXREF* × *GASR*, *TAXREF* × *APCTRL*, and *TAXREF* × *LCC* interaction terms are all significantly positive, demonstrating that the NO_x emissions tax reform has a more pronounced effect in cities implementing stronger environmental governance measures, demonstrating beneficial synergies between the NO_x tax and other environmental policies.

4.6 Mechanism Analyses (Mediating Effects)

4.6.1 Original Mediating Effect Analyses

This study employs the mediating effect analysis method described below to test hypotheses H1-a and H1-b.

First, we use the following model to perform the first step of regression:

$$M_{i,t} = \mathrm{a}\ TAXREF_{i,t} + X_{i,t}\beta + f_i + \mu_t + \varepsilon_{i,t}. \quad (6)$$

The *TAXREF* variable's parameter a in equation (6) characterizes the NO_x emissions tax rate reform's impact on mediating variable *M* (effect a). We use the following model for the second step of the regression:

$$CE_{i,t} = \mathrm{c}'\ TAXREF_{i,t} + \mathrm{b}M_{i,t} + X_{i,t}\beta + f_i + \mu_t + \varepsilon_{i,t}, \quad (7)$$

where coefficient *b* of mediating variable *M* denotes its impact on *CE* (effect *b*), and the mediating effect (indirect effect) of *M* can be measured using $a \times b$. c' denotes the direct effect of *TAXREF* on *CE* (effect c'), while the coefficient of *TAXREF* in the baseline regression (Model A) corresponds to the total effect (effect *c*). Theoretically, $c - c' = a \times b$ holds.

We use green patent application and technology (*GPAT*) as the mediating variable to test H1-a, measured by the number of sample cities' green invention patents per capita (data sourced from the Chinese National Intellectual Property Administration website).

To test H1-b, we employ industrial agglomeration as the mediator (*INDAGG*). Higher environmental tax rates accelerate existing "two highs"[①] (high energy consumption and high emissions) industrial firms' relocation and deter new firms from entering. Therefore, we define the numerator of *INDAGG* as the net entries of two highs firms, which we calculate as the annual number of new firms minus those that exit due to relocation, cancellation, or closure. To control for other factors affecting total firm counts, we divide this value by the net entry of all firms to obtain the formal *INDAGG* indicator. Data are sourced from public records released by China's State Administration for Market Regulation.

If H1-b holds, then a higher *TAXREF* should reduce the numerator (net entries of two highs

[①] According to the Chinese Ministry of Ecology and Environment, two highs industries cover coal power, petrochemical, chemical, steel, non-ferrous metal smelting, and building materials sectors. Source: https://www.mee.gov.cn/xxgk2018/xxgk/xxgk03/202105/t20210531_835511.html.

firms) by a larger proportion than the denominator (net entries of all firms), lowering the *INDAGG* value.

To save space and improve the research flow, mediating effect test results are presented in schematic diagrams (Figs. 6–8). The complete mediating effect analysis results are provided in Appendix Table A.8.

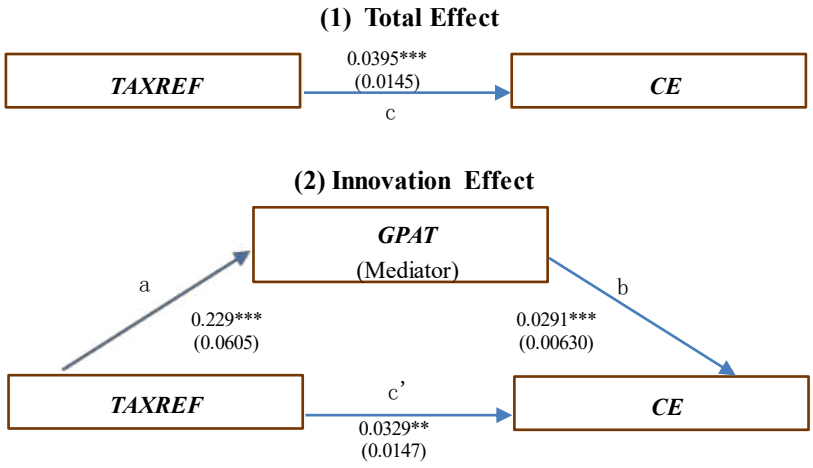


Fig. 6 Mediating effect analysis on the innovation effect (H1-a)

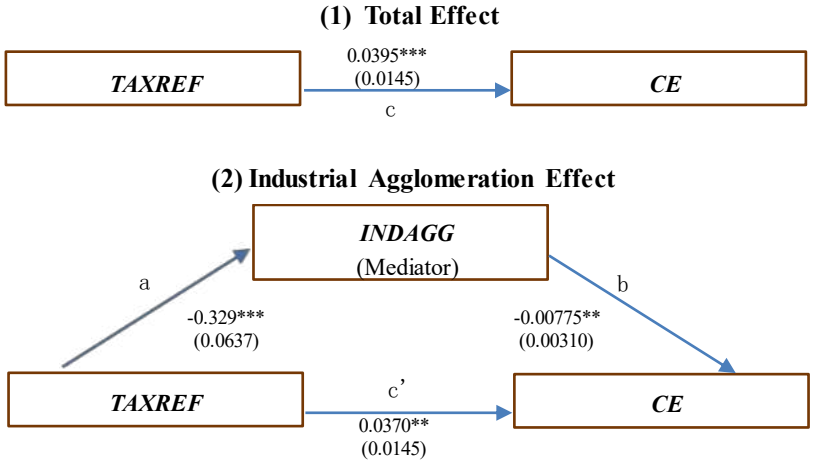


Fig. 7 Mediating effect analysis on the industrial agglomeration effect (H1-b)

As shown in the first-stage regression of Fig. 6, the impact of *TAXREF* on *GPAT* (effect *a*) is significantly positive (p-value ≤ 0.01). The second-stage regression reveals that the effect of

GPAT on *CE* (effect *b*) is significantly positive (p-value ≤ 0.01). The indirect effect ($a \times b$), estimated using the bootstrap method (Wen and Ye, 2014), is 0.00667 (p-value≤0.01). The direct effect of *TAXREF* on *CE* (c') decreases compared with the total effect (effect *c*) (coefficient drops from 0.0395 to 0.0329). These results confirm that technological innovation is a mediator through which the NO_x emissions tax rate reform promotes CE progress, validating H1-a. Furthermore, Fig. 7 shows that the impact of *TAXREF* on *INDAGG* (effect *a*) is significantly negative (p-value ≤ 0.01). The second-stage regression indicates that the effect of *INDAGG* on *CE* (effect *b*) is also negative (p-value ≤ 0.05). We employ the bootstrap method to estimate the indirect effect of *INDAGG* ($a \times b$), yielding a value of 0.00255 (p-value ≤ 0.01). The impact of *TAXREF* on *CE* (effect $c' = 0.0370$) is smaller than the total effect ($c = 0.0395$). These results indicate that the NO_x emissions tax rate reform accelerates CE progress by inhibiting the agglomeration of industrial production activities, confirming H1-b, albeit the effect is relatively weak.

4.6.2 Multiple Mediating Effect Analysis

To test the synergistic emissions reduction effect, this study uses the multiple mediating analysis described below to test H1-c.

First, we use the following two models for the first and second regression steps to estimate the respective impact of *TAXREF* on mediating variables M^1 and M^2:

$$M_{i,t}^{e} = \mathrm{a}_e TAXREF_{i,t} + X_{i,t}\beta + f_i + \mu_t + \varepsilon_{i,t} \;;\; e \in \{1,\ 2\}, \tag{8}$$

where a_1 and a_2 represent the respective effects of NO_x emissions tax reform on M^1 and M^2.

We then use the following model for the third step regression:

$$CE_{i,t} = \mathrm{c}'\, TAXREF_{i,t} + \mathrm{b}_1 M_{i,t}^{1} + \mathrm{b}_2 M_{i,t}^{2} + X_{i,t}\beta + f_i + \mu_t + \varepsilon_{i,t}, \tag{9}$$

where b_1 and b_2 represent the effects of mediating variables M^1 and M^2 on *CE*. Following Taylor et al. (2008), the combined mediating total indirect effect of the two types of mediating variables is $a_1 \times b_1 + a_2 \times b_2$. The value of parameter c' represents the direct effect of

TAXREF on *CE*. Theoretically, $a_1 \times b_1 + a_2 \times b_2$ should hold.

To test H1-c, we use CO_2 emissions intensity (*CO2PY*) and NO_x emissions intensity (*NOxPY*) as mediating variables M^1 and M^2, respectively. M^1 is measured by the CO_2 emissions per unit of GDP in sample cities ($CO_{2\ i,t}$ / $GDP_{i,t}$), and M^2 is measured by NO_x emissions per unit of GDP ($NO_{x\ i,t}$ / $GDP_{i,t}$). The data sources and processing methods are consistent with those used for carbon emissions data in the *CE* calculation.

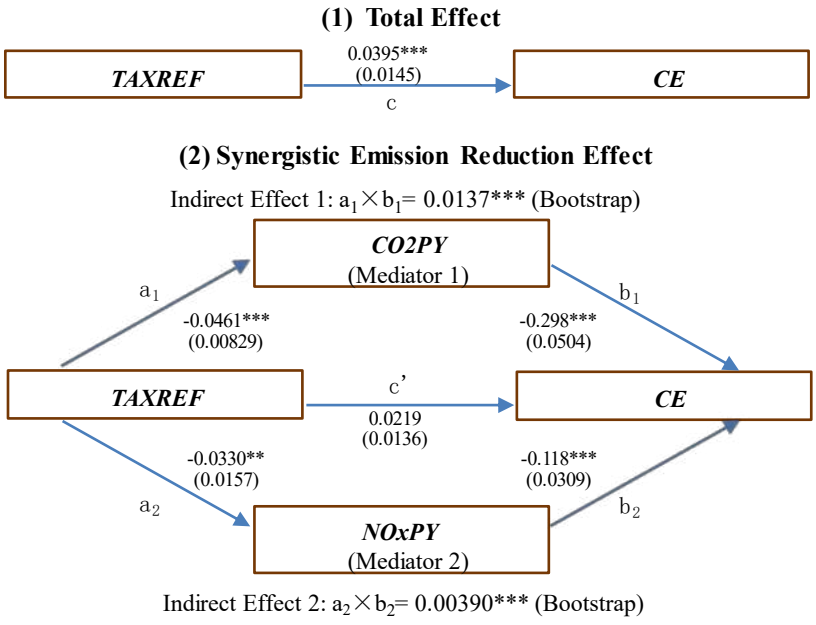


Fig. 8 Multiple mediating effect analysis on the synergistic emissions reduction effect (H1-c)

Fig. 8 illustrates the synergistic emissions reduction effect of the NO_x emissions tax rate reform. First, the effects *TAXREF* on *CO2PY* and *NOxPY* (effects a_1 and a_2) in the first- and second-stage regressions are significantly negative (p-values ≤ 0.05), and the effects of the two mediating variables on *CE* (effects b_1 and b_2) in the third-stage regression are also negative (p-values ≤ 0.01). This indicates that NO_x emissions tax rate reform simultaneously suppresses NO_x and CO_2 emissions, and this suppression contributes to accelerating CE

progress. Through 5,000 bootstrap replications, the total indirect effect ($a_1 \times b_1 + a_2 \times b_2$) equals 0.0176 (p-values ≤ 0.01), the direct effect ($c' = 0.0219$) is weaker than the total effect ($c = 0.0395$) and becomes insignificant, demonstrating full mediation. Therefore, the NO_x tax rate reform accelerates CE gains through synergistic CO_2–NO_x emissions reduction, confirming H1-c.

5. Conclusions

This study confirms that local adoption of NO_x emissions tax rates above the national minimum raises CE by 3.95%. The reform delivers stronger effects in eastern China and cities with larger secondary industry shares. It also interacts positively with clean energy promotion, air pollution control plans, and Low-Carbon City pilots. Mechanism tests reveal that the reform operates through green technological innovation, reduced industrial agglomeration, and, most importantly, synergistic NOx and CO_2 reduction, highlighting the ancillary CE benefits of pollutant tax and implying that integrating the NO_x tax with carbon pricing mechanisms could yield greater efficiency gains. These results offer practical means to integrate emissions control in developing countries.

Four policy implications emerge from our findings. First, our findings clarify the NO_x emissions tax as a supplementary carbon reduction tool and promotes subsequent rate reform. Based on pilot city experiences, policymakers should encourage more regions to adopt rates above the statutory minimum, using economic incentives to drive corporate emissions cuts.

Second, differentiated regional policies and enhanced coordination should be implemented to use the NO_x tax reform to advance industrial structure optimization. Stricter industrial entry thresholds and higher NO_x tax rates should be applied in eastern and industrial-heavy cities according to local environmental capacity, guiding high-emissions firms to regions with ample environmental capacity to prevent the concentration of polluting industries and

associated challenges in specific regions.

Third, technological innovation incentives should be developed, offering tax credits for R&D, technology transactions, or environmental equipment investment to firms engaged in synergistic NO_x and CO_2 reduction R&D or tech importing. Tax revenue should be allocated to special funds to promote clean energy transitions and green tech innovation and reinforce tech innovation's mediating effect.

Fourth, a synergistic emissions reduction monitoring system should be considered to unify NO_x and CO_2 emissions monitoring and control in tax collection. Provide preferential tax rates or refunds to firms exhibiting superior synergistic reduction to reinforce the policy orientation that pollution emissions reduction equals carbon reduction.

A potential limitation of this study is the lack of prefecture-level environmental tax data, which makes it difficult to re-verify findings using indicators such as total NO_x emissions tax collected or effective tax rates. Future research will endeavor to expand the data and our research to areas such as SO_2, soot, and water pollutants.

Acknowledgements

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