Supplementary Information

Synergistic Efficiency in Greenhouse Gas Emission Reduction and Water Pollution Control: Evaluating Policy Impacts in China

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Note S1. Method for calculating the GHG emission intensity of WWTPs

1.1 Data sources

The method for calculating the GHG emission intensity of WWTPs was conducted from 2009 to 2019. Following relevant literature and the Intergovernmental Panel on Climate Change (IPCC) algorithm (Gitarskiy and Climatology, 2019; Guo et al., 2019; Wang et al., 2022; Du et al., 2023), influent COD concentration, influent TN concentration, and emission factors are determined. When using plant-level data to calculate methane emissions, samples with negative results are deleted due to the uncertainty of sludge moisture content and organic matter content.

1.2 Boundary of GHG emission accounting system

In this study, the accounting boundary of GHG emissions from wastewater treatment plants is direct emissions ($\mathrm{CH_4}$ and $\mathrm{N_2O}$) and indirect emissions ($\mathrm{CO_2}$ generated by electricity consumption) in the wastewater treatment process.

1.3 Steps for calculating the GHG emission intensity

1.3.1 Direct GHG emission calculation

(1) The $\mathrm{CO_2eq}$ of $\mathrm{CH_4}$ emission during the treatment process

$$M_{\mathrm{CH_4}} = (COD_{\mathrm{inf}} \times T \times 10 - S \times p) \times F_{\mathrm{CH_4}} - R_{\mathrm{CH_4}} \tag{S1}$$

where $M_{\mathrm{CH_4}}$- direct emissions of $\mathrm{CH_4}$, kg

COD_{inf}- the influent organic matter, mg/L. When calculating $\mathrm{CH_4}$ emissions in a city, this study uses the provincial average of the total amount of influent organic matter instead.

T- the total amount of wastewater inflow into the biological unit, assuming that there is no overflow or crossing after the primary treatment, is replaced by the annual amount of wastewater treatment volume, $10000 m^3$

S- annual total dry sludge production of WWTPs, t

p- the organic matter content of dry sludge, %. This study assumes that the organic matter content in the sludge is 40% and the water content is 75%, p is set to 0.1.

F_{CH_4}- emission factor of CH_4 during the treatment process, $kgCH_4/kgCOD$. Settings are adjusted for different provinces based on references (Cai et al., 2015).

R_{CH_4}- the CH_4, which is recovered and reused, is taken as 0

$$E_{CH_4} = M_{CH_4} \times f_{CH_4} \tag{S2}$$

E_{CH_4}- the CO_2eq of CH_4 emission, $kgCO_2eq$

f_{CH_4}- the 100-year GWP of CH_4 is 28

(2) The CO_2eq of N_2O emission during the treatment process

$$M_{N_2O} = \Delta TN \times T \times 10 \times F_{N_2O} \times \frac{44}{28} \tag{S3}$$

where M_{N_2O}- direct emissions of N_2O, kg

ΔTN- the nitrogen removal of a municipal wastewater treatment plant, mg/L. When calculating CH_4 emissions in a city, we use the provincial average of the total amount of nitrogen removal instead.

T- annual amount of wastewater treatment volume, $10000\ m^3$

F_{N_2O}- emission factor of N_2O during the treatment process, it is set to 0.035 kg N_2O/kg TN

$$E_{N_2O} = M_{N_2O} \times f_{N_2O} \tag{S4}$$

E_{N_2O}- the CO_2eq of N_2O emission, $kgCO_2eq$

f_{N_2O}- the 100-year GWP of N_2O is 265

1.3.2 Indirect GHG emission calculation

$$M_{CO_2} = T \times W \times F_{CO_2} \tag{S5}$$

where M_{CO_2}- CO_2 generated by electricity consumption, kg

T- WWTPs annual total wastewater treatment volume of a city, 10000 m^3

W- electricity consumption per unit of wastewater treatment at different scales, kWh/m^3. Settings are adjusted for different wastewater volumes (Yan et al., 2019).

F_{CO_2}- emission factor of CO_2 during the treatment process, kg/kWh

1.3.3 GHG emission intensity calculation

$$\begin{aligned} GHG_{\text{total}} &= GHG_{\text{direct}} + GHG_{\text{indirect}} \\ &= E_{CH_4} + E_{N_2O} + M_{CO_2} \end{aligned} \tag{S6}$$

$$\text{GHG emission intensity} = \frac{GHG_{\text{total}}}{T} \tag{S7}$$

where $\text{GHG}_{\text{total}}$- total GHG emission, kg

$\text{GHG}_{\text{direct}}$- direct GHG emission of CH_4 and N_2O from the treatment process, kg

$\text{GHG}_{\text{indirect}}$- indirect GHG emission of CO_2 from the consumption of electricity, kg

Note S2. Logarithmic Mean Divisia Index decomposition method

The Kaya identity can decompose GHG emissions into energy, economy, and population (Chen et al., 2018). The Logarithmic Mean Divisia Index (LMDI) method is commonly employed to analyze the contribution of individual factors when multiple drivers act synergistically (Ang, 2015; Huang et al., 2023; Yang et al., 2025). Due to its comprehensive decomposition without residual terms, LMDI is frequently combined with the Kaya identity for GHG emission studies. This study employed the additive decomposition method of the LMDI model (Ang, 2004). As shown in Equation (S8), wastewater GHG emissions are decomposed into five drivers: GHG emission of energy consumption effect (C), technological development effect (T), industrial structure effect (I), economic development effect (G), and population effect (P). Specifically, C represents the ratio of wastewater GHG emissions to total energy consumption in year t, T denotes the ratio of total energy consumption to value-added of secondary industries, I indicates the proportion of secondary industry value-added to GDP, G stands for per capita GDP, and P represents total population.

$$\begin{aligned} E_{\text{GHG}}^{t} &= \frac{E_{\text{GHG}}^{t}}{EC^{t}} \times \frac{EC^{t}}{IV^{t}} \times \frac{IV^{t}}{GDP^{t}} \times \frac{GDP^{t}}{P^{t}} \times P^{t} \\ &= C^{t} \times T^{t} \times I^{t} \times G^{t} \times P^{t} \end{aligned} \tag{S8}$$

$$\begin{aligned} \Delta E_{\text{GHG}} &= E_{\text{GHG}}^{t} - E_{\text{GHG}}^{0} \\ &= \Delta E_{C} + \Delta E_{T} + \Delta E_{I} + \Delta E_{G} + \Delta E_{P} \end{aligned} \tag{S9}$$

$$\Delta E_{i} = \frac{E_{\text{GHG}}^{t} - E_{\text{GHG}}^{0}}{\ln E_{\text{GHG}}^{t} - \ln E_{\text{GHG}}^{0}} \times \ln \frac{{E_{i}}^{t}}{{E_{i}}^{0}} \quad (i = C,\ T,\ I,\ G,\ P) \tag{S10}$$

$$S=\frac{\Delta E_{\text{GHG}}/E_{\text{GHG}}^{0}}{\Delta E_{\text{Pollution}}/E_{\text{Pollution}}^{0}} \tag{S11}$$
$$=\frac{(E_{\text{GHG}}^{t}-E_{\text{GHG}}^{0})/E_{\text{GHG}}^{0}}{(E_{\text{Pollution}}^{t}-E_{\text{Pollution}}^{0})/E_{\text{Pollution}}^{0}}$$
$$=\Delta E_C\times\frac{E_{\text{Pollution}}^{0}}{\Delta E_{\text{Pollution}}\times E_{\text{GHG}}^{0}}+\Delta E_T\times\frac{E_{\text{Pollution}}^{0}}{\Delta E_{\text{Pollution}}\times E_{\text{GHG}}^{0}}+\Delta E_I\times\frac{E_{\text{Pollution}}^{0}}{\Delta E_{\text{Pollution}}\times E_{\text{GHG}}^{0}}$$
$$+\Delta E_G\times\frac{E_{\text{Pollution}}^{0}}{\Delta E_{\text{Pollution}}\times E_{\text{GHG}}^{0}}+\Delta E_P\times\frac{E_{\text{Pollution}}^{0}}{\Delta E_{\text{Pollution}}\times E_{\text{GHG}}^{0}}$$
$$=S_C+S_T+S_I+S_G+S_P$$

Equation (S9) presents the LMDI decomposition model, illustrating how changes in wastewater GHG emissions from the base year to year t are decomposed into these five effects. Equation (S10) and Equation (S11) demonstrate the calculation method for contributions of these drivers, where ΔE_i denotes the effect of the i-th driver from the base year to year t.

Note S3. The main content of the "10-Point Water Plan"

The "10-Point Water Plan" of China is a stricter water policy formulated to address water pollution issues and achieve long-term water resource protection and management. The main measures of this policy include: (1) Comprehensive control of pollutants discharge; (2) Promoting transformation and upgrading of economic structural; (3) Emphasis on saving and protecting water resources; (4) Strengthening scientific and technological support; (5) Playing the full role of market mechanism; (6) Strict enforcement of environmental regulations; (7) Strengthening the management of water environment; (8) Ensuring the security of water ecological environment; (9) Clarifying and implementing responsibilities; (10) Strengthening public participation and social supervision (Zhou et al., 2021).

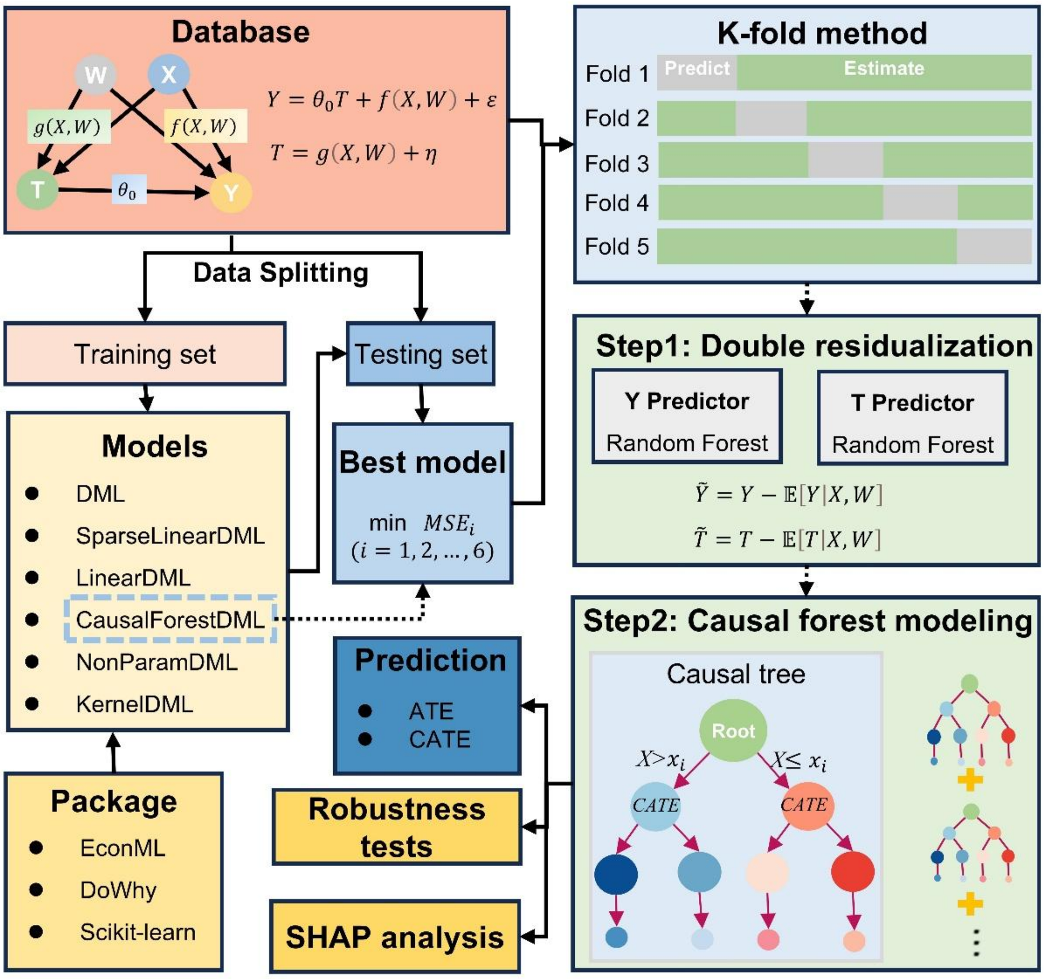

Fig. S1 The flowchart of Causal Forest DML.

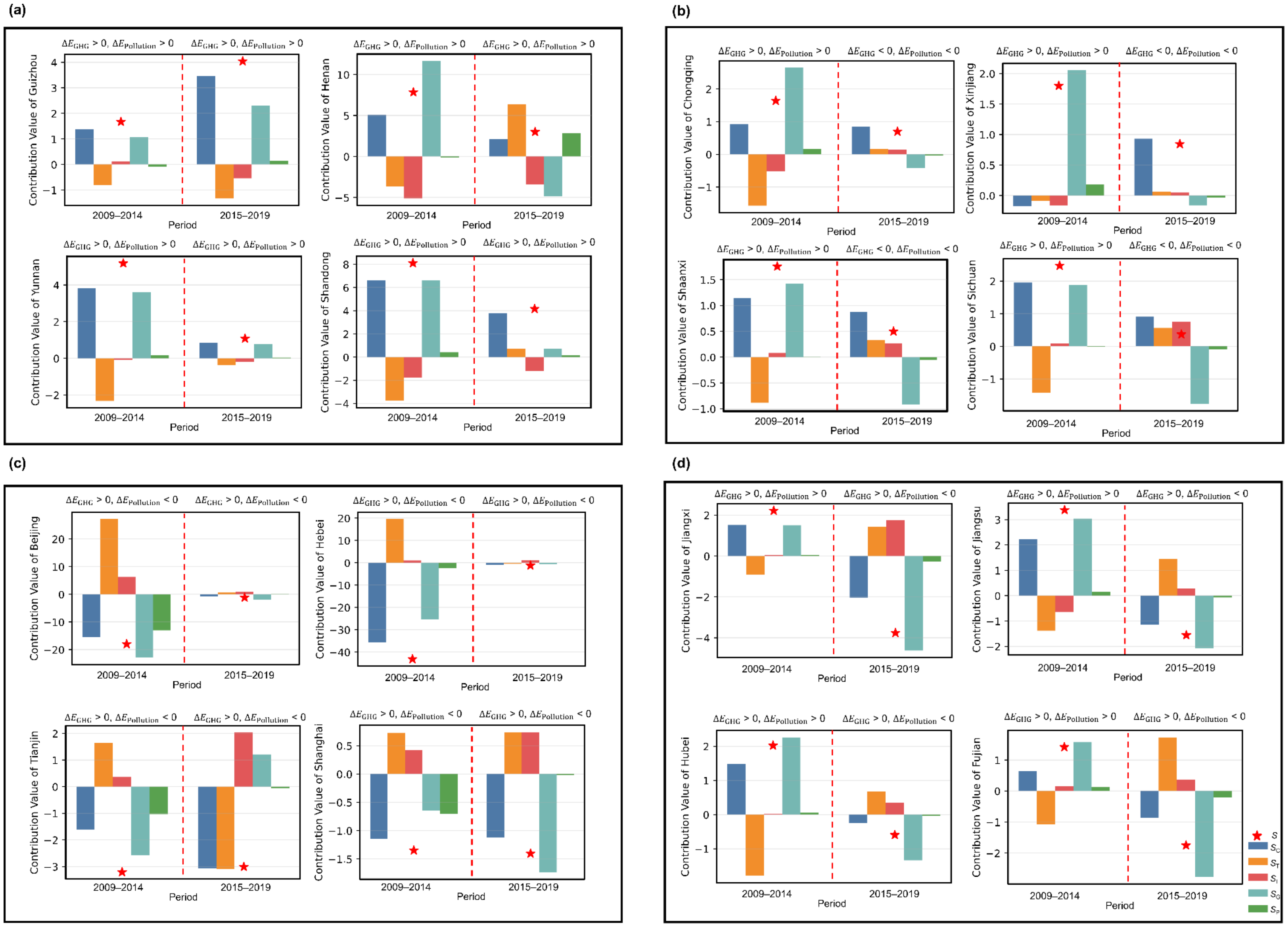

Fig. S2 Synergistic efficiency and the contributions of five factors across two stages at the provincial level.

Table S1. Coefficients of effluent pollutant discharge equivalent

Substances	Equivalent coefficient	Value
COD_{Cr}	δ_1	1
BOD_5	δ_2	1/0.5
SS	δ_3	1/4
NH_3-N	δ_4	1/0.8
TP	δ_5	1/0.25

Notes:

The effluent pollutant discharges equivalent coefficient values of all pollutants are from the Environmental Protection Tax Law of the People's Republic of China (https://www.mee.gov.cn/ywgz/fgbz/fl/201811/t20181114_673632.shtml).

Table S2. The main data sources in our study

Used in	Data	Sources
GHG emission intensity calculation	Influent COD concentration	(Du et al., 2023)
	Influent TN concentration	
	Effluent TN concentration	
	Electricity consumption	
	Wastewater treatment volume	
	Sludge yield	
	Emission factor of CH_4	(Cai et al., 2015)
	Emission factor of N_2O	(Guo et al., 2019)
	Emission factor of CO_2	(Wang et al., 2022)
	Electricity consumption per unit of wastewater treatment volume at different scales	(He et al., 2019)
	City's quantity of dry sludge produced City's quantity of wastewater treated	China Construction Statistical Yearbook
LMDI	Total energy consumption	China Energy Statistical Yearbook
	Value-added of secondary industries Gross domestic product Total population at the end year	We get the data from Chinese Research Data Services (CNRDS) Platform
DML	Population density	
	The proportion of secondary industry in GDP	
	Average employee salaries	
	Industrial energy use efficiency (electricity consumption per unit of industrial output value)	
	The number of green patents	
	Scientific research expenditure	China City Statistical Yearbook
	Drainage investment	China Construction Statistical Yearbook
	Total water supply	
	The proportion of sewer length	
	The number of wastewater treatment plants	
	Wastewater treatment rate	
	Total water resources	China Environmental Statistical Yearbook

Table S3. Comparing wastewater GHG estimations in this study with existing literature

Sources	Types	Accounting results										
		2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
(Du et al., 2023)[a]	GHG emissions (Mt CO_2eq)	22.37	22.37	26.51	29.59	31.51	32.98	36.15	38.52	39.60	43.30	46.24
(Guo et al., 2019**)**[b]		14.30	17.90	20.80	23.10	24.90	280	29.80	31.40	-	-	-
(Huang et al., 2023)[c]		19.86	23.81	27.23	29.05	31.38	34.7	39.02	42.14	44.40	50.36	58.30
(Wang et al., 2022)[d]		15.34	16.72	20.58	20.42	22.30	24.07	24.44	24.47	26.34	28.12	30.30
(Yang et al., 2023**)**[b]		18.60	20.00	21.23	22.27	23.43	24.83	26.05	27.06	27.79	28.84	30.06
All reference		[14.30, 22.37]	[16.72, 23.81]	[20.58, 27.23]	[20.42, 29.59]	[22.30, 31.51]	[24.07, 34.70]	[24.44, 39.02]	[24.47, 42.14]	[26.34, 44.40]	[28.12, 50.36]	[30.06, 58.30]
Our method		13.17	16.81	19.67	21.88	23.62	26.61	28.34	29.10	31.19	34.417	38.73
(Du et al., 2023)[a]	GHG emission intensity (kg CO_2/m^3)	0.66	0.69	0.68	0.68	0.69	0.70	0.72	0.71	0.74	0.73	0.77
(Guo et al., 2019**)**[b]		0.53	0.54	0.54	0.55	0.66	0.58	0.59	0.581	-	-	-
(Huang et al., 2023)[c]		-	-	-	-	-	-	-	-	-	-	-
(Wang et al., 2022)[d]		0.64	0.56	0.54	0.53	0.52	0.52	0.49	0.45	0.45	0.45	0.45
(Yang et al., 2023**)**[b]		0.59	0.56	0.54	0.521	0.523	0.523	0.516	0.511	0.5	0.49	0.478
All reference		[0.53, 0.66]	[0.54, 0.69]	[0.54, 0.68]	[0.52, 0.68]	[0.52, 0.69]	[0.52, 0.70]	[0.49, 0.72]	[0.45, 0.71]	[0.45, 0.74]	[0.45, 0.73]	[0.45, 0.77]
Our method		0.50	0.51	0.52	0.52	0.53	0.57	0.56	0.56	0.56	0.57	0.59

a. System boundary is the entire process of municipal wastewater management, from wastewater collection, treatment, and environmental discharge to sludge disposal.

b. System boundary is the total emissions of CH_4 and N_2O from biological treatment and CO_2 from electricity.

c. System boundary is collection and treatment, sludge treatment and disposal, discharged treatment wastewater, electricity use, and chemical use.

d. System boundary is the total GHG emissions of different technologies from biological treatment processes, electricity consumption, and discharge pathways.

Notes:

Notably, divergent system boundaries across studies lead to variations in reported GHG emissions. For instance, Huang et al. (2023), which adopts the most comprehensive boundary encompassing sludge disposal, chemical consumption, and the entire process of municipal wastewater management, from wastewater collection, treatment, and environmental discharge to sludge disposal, reports higher total GHG emissions compared to studies with narrower boundaries. The results align closely with Guo et al. (2019) and Yang et al. (2023), both of which share comparable system boundaries focusing on: i) Direct CH_4 and N_2O emissions from biological treatment processes; ii) Indirect CO_2 emissions from electricity consumption. The analysis reveals that the emission intensities calculated in this study for 2012–2019 fall within the range of all references, while earlier estimates (2009–2011) approach the lower bounds of this range. Although uncertainties persist in the accounting results, the methodological consistency across reference studies and our work ensures robust comparative validity.

Table S4. Results of model selection

Explained variable	Model	MSE
Wastewater GHG emission intensity	DML	0.000918
	LinearDML	0.000918
	SparseLinearDML	0.000920
	CausalForestDML	**0.000910**
	NonParamDML	0.003476
	KernelDML	0.000918
Wastewater treatment rate	DML	0.008361
	LinearDML	0.008361
	SparseLinearDML	0.008360
	CausalForestDML	**0.008325**
	NonParamDML	0.022949
	KernelDML	0.008373

Notes:

The algorithm with the lowest *MSE* would be selected. The formula for calculating *MSE* is Eq. (S12). This study employed 5-fold cross-validation to avoid overfitting.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad \text{(S12)}$$

where y_i is the real value of Y, $\hat{y}_i$ is the predicted value of Y, and n is the number of samples.

Table S5. Results of the robustness test of Causal Forest DML

Explained variable	Refutation	Original effect	New effect	Result
Wastewater GHG emission intensity	Placebo treatment	0.016	0.001	Pass (Almost zero effect)
	Random common cause	0.016	0.017	Pass (Not changed effect)
	Data subset	0.016	0.021	Pass (Not changed effect)
Wastewater treatment rate	Placebo treatment	0.034	-0.003	Pass (Almost zero effect)
	Random common cause	0.034	0.035	Pass (Not changed effect)
	Data subset	0.034	0.031	Pass (Not changed effect)

Notes:

To validate the robustness of the estimated effect, three refutation tests were employed. The first method is the placebo test, which involves randomly assigning treatment variables that impact the outcome, if there is a large difference between the new estimated causal effect and the original estimated effect, it indicates that the original analysis is robust. The new effect of placebo test is close to zero, indicating that our model successfully passed the placebo test.

The second method is the random common cause refutation method, which involves introducing a new independent variable and then estimating the causal effect. The purpose of introducing a random common cause is to test for the presence of unaccounted confounding factors, and if the newly estimated causal effect is the same as the original causal effect, it indicates that the initial causal effect is robust (Kang et al., 2024).

The third approach is the data subset refutation method, which verifies the robustness of the model by looking at whether the estimated causal effects are consistent across different data subsets (Fu et al., 2024; Kang et al., 2024; Wei et al., 2024).

When introducing a random common cause and substituting a random subset, the new effect remains comparable to the original effect, demonstrating the efficacy of our model in passing these tests.

Table S6. Robustness testing based on parallel policy

Variable	Y = wastewater GHG emission intensity			Y = wastewater treatment rate		
	(1)	(2)	(3)	(1)	(2)	(3)
T	0.016***	0.014***	0.015***	0.043***	0.038***	0.037***
Control (Smart City)	No	Yes	No	No	Yes	No
Control (Low-carbon City)	No	No	Yes	No	No	Yes

[a] *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Notes:

China announced the pilot lists of “Smart City” in 2013 and 2014, respectively, and carried out three batches of “Low-carbon City” pilot work in 2010, 2012, and 2017 in order to strengthen the construction of a low-carbon society. Results show that dummy variables indicating whether a city is a pilot city for the “Smart City” and “Low-carbon City” initiatives are added to the control variables to verify the accuracy of the model. By observing the robustness test results of the model, it can be seen that the ATE of the “10-Point Water Plan” on GHG emission intensity and wastewater treatment rate changed slightly but remains significant at the 99% confidence level, indicating that the conclusion drawn by the benchmark model in our study has not been interfered with by other policies.

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