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The impact of zero-waste city pilot policies on urban carbon reduction: Empirical evidence from double machine learning approach

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Abstract

The construction of zero-waste cities is an important driver for achieving the "dual carbon" goals on schedule and for advancing ecological civilization to a higher level. Based on data from 287 cities in China from 2010 to 2022, a dual machine learning model was employed to empirically examine the impact of zero-waste city construction on urban carbon emissions, using the pilot policy as a quasi-natural experiment. The research yields the following conclusions: (1) The implementation of the zero-waste city policy significantly reduces carbon emissions in pilot areas. This conclusion remains robust after a series of tests, including adjustments to the research sample, reconfiguration of the dual machine learning model, and sensitivity analyses. (2) The policy has a more pronounced effect in reducing carbon emissions in major eco-friendly cities, non-resource-based cities, and old industrial base cities, compared to non-major eco-friendly cities, resource-based cities, and non-old industrial base cities. (3) Improvements in science and technology research and internet development levels enhance the carbon reduction effect of zero-waste city initiatives. These findings provide valuable insights for promoting the governance of urban solid waste and achieving the "dual carbon" goals in a coordinated manner.

Keywords: Zero-waste city; Urban carbon emissions; Double machine learning

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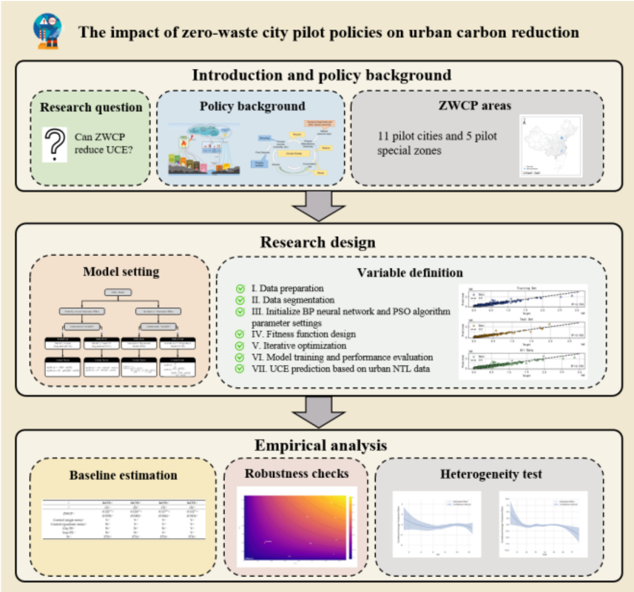
Graphical abstract



1. Introduction

Over the past two decades, global resource consumption and environmental pressures have intensified, accompanied by increasingly pronounced ecosystem degradation (Schmidt & Laner, 2025). In 2023, the global average temperature rose by approximately 1.45°C above pre-industrial levels, accompanied by a rise in the frequency of extreme heat events (Goren *et al.*, 2023). According to a United Nations report, humans generate over 1 million kilograms of urban solid waste every minute, and the accumulation of plastics, construction debris, and food waste exacerbates land and ocean pollution (Starczewska *et al.*, 2024). Reducing greenhouse gas emissions, primarily carbon dioxide, has become a central policy priority for mitigating this crisis and advancing sustainable development (Wu *et al.*, 2016). In this context, the concept of "zero-waste cities", which emphasizes resource recycling and waste reduction at the source, offers a systematic pathway for carbon reduction at the urban level (H. Wang *et al.*, 2025). The General Office of the State Council issued the the Zero-Waste City Pilot (ZWCP) Work Plan in December 2018, aiming to alleviate the ecological pressures caused by solid waste through green development models. The Ministry of Ecology and Environment first announced a list of 11 pilot "zero-waste cities" in 2019 and expended the list during the 14th Five-Year Plan period in 2022 to include additional cities, thereby broadening the scope of the pilot program (Qian *et al.*, 2025). However, as an important institutional innovation to address excessive resource consumption and ecological degradation, the carbon reduction effect of the zero-waste city pilot policy has not yet been sufficiently examined using rigorous causal inference approaches. Accordingly, rigorous identification and evaluation of its carbon reduction effects are crucial for validating policy effectiveness and optimizing low-carbon governance strategies.

Urban carbon emissions (UCE) are not only a key environmental indicator for measuring the severity of the climate crisis, but also a crucial metric to assess the quality of economic development and the level of ecological civilization (Bai *et al.*, 2023). The academic community has conducted multidimensional and cross-disciplinary empirical research on the governance paths of carbon emissions, particularly focusing on the emission reduction effects of various policy tools. Using the low-carbon city pilot as a quasi-natural experiment, Yu and Zhang (2021) demonstrate that the policy significantly improves urban carbon emission efficiency, thus inhibiting carbon emission growth. C. Li *et al.* (2022) found that the National Emissions Trading System (ETS) indirectly suppresses the expansion of UCE by enhancing green total factor productivity. Zhang *et al.* (2023) verified that the green finance reform and innovation pilot zone effectively reduces both industrial energy consumption and carbon emissions through green technology innovation and capital flow adjustment. Du *et al.* (2023), in their study of the Energy Quota Trading (EQT) pilot, highlighted that the system not only alleviates energy mismatches and incentivizes green innovation, but also continuously improves carbon emission efficiency three years after implementation. Jiang & Sun (2024) demonstrated, using a dual machine learning model, that the construction of smart cities significantly promotes urban green development through industrial upgrading, resource optimization, and technological innovation, thereby achieving a synergistic effect on carbon emission reduction. With the Healthy City pilot as a quasi-natural experiment, Z. Guo & Zhang (2023) found that the policy reduced per capita CO_2 emissions by approximately 8.8%, significantly improving air quality by reducing industrial emissions and enhancing public green infrastructure.

The ZWCP programme is a key driver for achieving the goals related to reducing solid waste at the source, promoting waste recycling, and enabling synergistic carbon reduction. Existing studies have examined the implementation effects of the ZWCP policy from multiple perspectives, yielding a range of informative empirical findings. Using 278 prefecture-level cities as samples, Bi *et al.* (2024) found that pilot projects significantly boosted green technology innovation through DID and causal forest methods, yielding positive outcomes via increased research and development investment and information technology upgrades. Q. Chen *et al.* (2025) constructed a "Five-Dimensional Multi-Index" classification framework to systematically review the governance practices of the first 16 pilot cities, providing operational indicators for horizontal comparison and policy evaluation. Y. Li & Li (2023) proposed an approach to transforming "construction indicators into evaluation indicators" and employed an obstacle degree model to identify management shortcomings, enriching the methods for pilot evaluation. Liu *et al.* (2024) further verified that the pilot policy significantly accelerates urban green and low-carbon transformation by incentivizing green innovation and generates positive spatial spillover effects on surrounding areas. Zhan *et al.* (2023) calculated the full lifecycle carbon footprint of typical zero-waste technologies through lifecycle analysis. Based on the material flow and emission coefficient method, Tian *et al.* (2025) estimated the overall reduction of CO_2 emissions from pilot projects, providing preliminary quantitative evidence for the policy's climate benefits.

However, most studies that evaluate UCE of the ZWCP rely on alternative metrics or simple regression tests; to date, no work has systematically embedded the policy within a causal-inference framework capable of isolating its true effect. The absence of rigorous causal identification not only weakens the credibility of policy extrapolation but also deprives subsequent mechanism studies of a solid empirical foundation. Measuring carbon emissions is inherently complex: beyond fuel consumption, it must integrate information on industrial structure, technological progress, population density and economic growth. When a large set of potential confounders must be controlled simultaneously, conventional econometric techniques are prone to the "curse of dimensionality", wherein estimators fail to converge once the number of control variables exceeds the logarithmic order of the sample size. In addition, relationships among variables may be nonlinear, whereas standard causal models typically assume linearity, limiting their applicability. Double machine learning (DML) offers a robust remedy. In its first stage, DML leverages flexible machine-learning algorithms to model and select high-dimensional covariates; through sample splitting and cross-fitting, it offsets the influence of prediction error on the causal parameter of interest, thereby preserving consistency and $\sqrt{n}$-rate convergence even in the presence of many controls. Accurately identifying the carbon-abatement effect of ZWCP will not only delineate the policy's net impact with greater precision but also provide the methodological bedrock for uncovering the underlying reduction, recycling and substitution pathways.

On this basis, the DML model was applied in this paper to analyze the impact of the ZWCP policy on UCE, with Chinese prefecture-level cities as the research object. First, a particle-swarm-optimized back-propagation neural network (PSO-BP) algorithm was used to fit and train the carbon emissions and nighttime lighting data to obtain complete UCE data. Second, the DML model was applied to examine the causal relationship between the ZWCP policy and UCE, and multiple robustness tests were conducted to ensure reliable inference. Finally, a heterogeneity analysis was conducted across two dimensions: city type and urban characteristics.

This study makes several notable contributions at both theoretical and empirical levels. First, from a methodological perspective, this paper combines a particle swarm optimization–backpropagation neural network with nighttime light remote sensing data to construct a spatiotemporal, continuous, and cross-city comparable UCE core indicator. This approach offers a replicable technical solution to address issues of missing carbon emission data and inconsistent data scales. Second, in terms of the identification strategy, a robust DML framework was systematically introduced to achieve quasi-causal estimation of the carbon emission reduction effect of the ZWCP in a complex high-dimensional covariate environment, effectively eliminating the inherent limitations of traditional regression in the face of the curse of dimensionality and multicollinearity, and enriching the cases of applying emerging machine learning methods in the field of environmental economics. Third, in terms of empirical results, the heterogeneity test on the two critical dimensions—city type and urban characteristics—revealed substantial and significantly significant differences in policy effects among various city types and characteristics, providing more targeted evidence to support zoning policies and refined carbon governance.

2. Policy Background

Sustained socio-economic development has led to an increase in the amount of solid waste; however, the global rate of proper treatment of solid waste remains low (L. Chen & Gao, 2025). **Figure 1** illustrates the environmental impact of uncontrolled solid waste incineration. Uncollected solid waste can contaminate soil, groundwater, and the atmosphere, with a portion ultimately flowing into the ocean, causing adverse effects on marine ecosystems. During uncontrolled incineration, waste is incompletely burned due to low temperatures and unstable conditions, which easily generate new toxic and harmful substances. Taking plastic products as an example, their combustion often produces dioxins (PCDD/Fs) and related compounds. These persistent organic pollutants can remain in the environment for several years and accumulate in the human body for ten years or even longer. Some compounds even impair brain function and disrupt the endocrine system (Gorczyca *et al.*, 2025). The long-term and pervasive harm caused by solid pollution has gradually led to a consensus among governments, research institutions, and the public that relying solely on end-of-pipe pollution treatment cannot fundamentally solve the underlying problem. Waste must be "eliminated" at the source through methods such as reduction and recycling (Sanchís *et al.*, 2025). This shift in governance thinking has facilitated the diffusion of the "zero waste" concept and encouraged context-specific approaches across countries and cities.

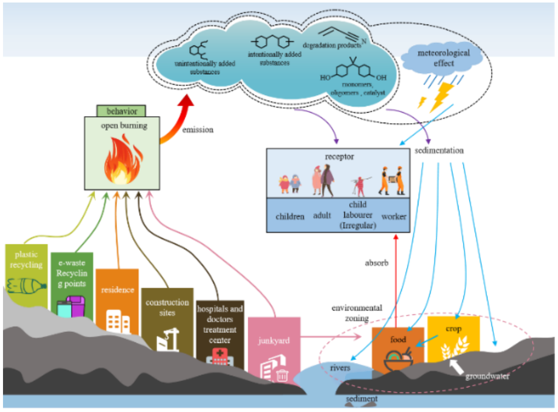


Figure 1. Environmental impacts of uncontrolled incineration of solid waste.

With the continuous deepening of the concept of sustainable development, "zero-waste" has gradually become a shared vision of the international community, manifesting in diverse practical models worldwide (Li *et al.*, 2026). Japan's construction of a zero-waste society is primarily grounded in the "Basic Law for Promoting the Formation of a Circular Society," fully implemented in 2001. The law mandates that all stakeholders adhere to the 3R principles—"Reduce, Reuse, and Recycle"—in waste management (see **Figure 2**), fully reflecting the need for extensive participation and support from all sectors of society in building zero-waste cities (Moshkal *et al.*, 2024). In 2014, the European Zero-Waste Alliance introduced an innovative seven-level waste management system to guide society towards higher quality, high-value source prevention and resource utilization of waste. The levels, from most advocated to the least acceptable, are as follows: rethinking and redesigning, reusing after damage, reusing after repair, recycling (including composting, anaerobic fermentation), physical and chemical recycling, residual waste management, and irreversible treatment. The entire management system strictly prioritizes reducing waste generated from the source and achieving maximum efficient resource utilization through strategically optimizing product design and improving production and consumption patterns. Methods such as incineration and landfilling are considered last resort options (Caro *et al.*, 2023). The system embodies the core concept that "the best waste is the waste that has not been generated," with important reference value in promoting the shift from traditional "waste management" to a more forward-looking approach of "resource management." Singapore proposed the vision of becoming a "zero-waste country" in its Sustainable Development Blueprint 2015, which soon expanded to the city level, prompting cities such as San Francisco, Vancouver, and Stockholm to develop their own "zero-waste city" blueprints (Qin *et al.*, 2022). Therefore, cultivating replicable and scalable demonstration projects based on ZWCP is essential for advancing the goals of ecological civilization and improving environmental quality.

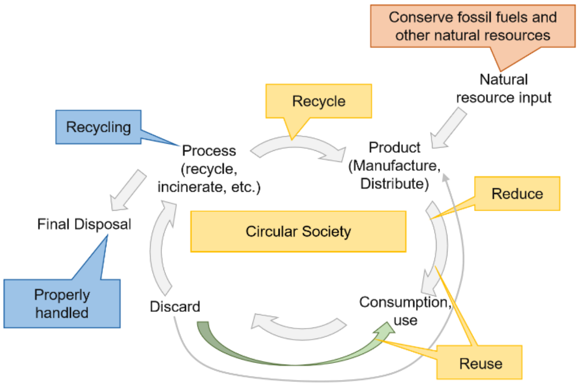


Figure 2. Impacts of uncontrolled solid waste incineration.

Inspired by prior experience, China has also begun to actively explore a development path for zero-waste cities suited to its national conditions. Guided by the new development concept of innovation, coordination, green growth, openness, and sharing, the zero-waste city initiative represents an urban development model that fosters green growth and sustainable lifestyles (Wang & Guo, 2026). It aims to continuously reduce solid waste at the source, maximize resource utilization, and minimize landfill volume and the environmental impact of solid waste (Dong *et al.*, 2022). The construction of zero-waste cities in China began in early 2018, with the strategic objective of minimizing urban solid waste, maximizing resource utilization, and ensuring safe disposal. In June of the same year, a central-level document identified zero-waste city development as a key task in pollution prevention and control. In December 2018, the General Office of the State Council issued a pilot program, planning to select approximately 10 cities to implement demonstration projects. In April 2019, the "11+5" pilot reform—featuring cities such as Shenzhen and Baotou, as well as related industrial parks and counties—was officially launched. In November 2021, the Ministry of Ecology and Environment, together with 17 other ministries, jointly issued opinions to further promote the classification and resource utilization of household waste. In December of the same year, authorities released a comprehensive program for the 14th Five-Year Plan period, confirming to the construction of zero-waste cities as an important lever for achieving carbon peaking and carbon neutrality, and building a cross-spatial and temporal indicator system, providing institutional support for achieving the modernization objective of harmonious coexistence between humans and nature. At present, the names of the zero-waste pilot areas in China are shown in **Table 1**, and the spatial distribution is shown in **Figure 3**.

Table 1. ZWCP areas.

Categories	Locations
Pilot cities	Baotou, Chongqing, Panjin, Ruijin, Sanya, Shaoxing, Shenzhen, Tongling, Weihai, Xuchang, Xining, Xuzhou
Pilot special zones	Beijing Economic and Technological Development Area, China-Singapore Tianjin Eco-City, Guangze, Xiong'an New Area

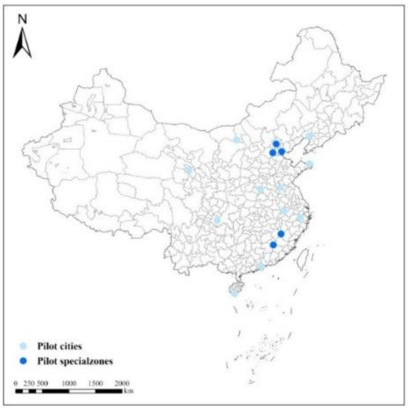


Figure 3. Distribution of ZWCP experimental zones.

3. Research design

3.1. Model setting

To systematically evaluate the impact of the ZWCP policy on UCE, the study employs the DoubleML package in a Python 3.12 environment, introducing the DML framework to identify causal effects. Compared to traditional methods, DML can effectively mitigate the "curse of dimensionality" and reduce model specification errors when dealing with high-dimensional control variables. The DML framework primarily incorporates two modes types: Partial Linear Regression (PLR) and Interactive Regression Model (IRM) (Bach *et al.*, 2021). The technical roadmap is shown in **Figure 4**.

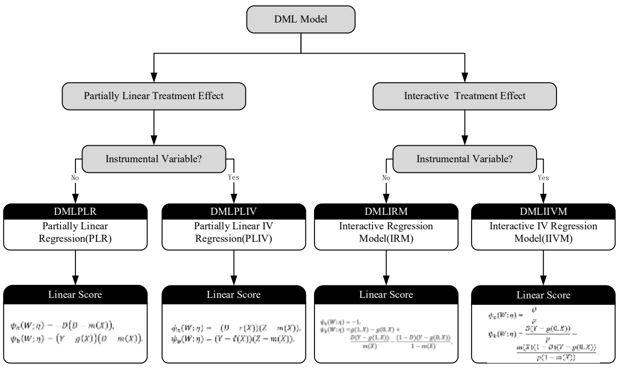


Figure 4. DML model framework.

The inference efficiency of PLR is considerably higher, and its orthogonalization score function does not include the potentially unstable reciprocal term. The doubly robust scoring function of IRM explicitly includes the reciprocal of the propensity score, which leads to a substantial increase in variance when the propensity score approaches extreme or near-zero values, so the overall inference efficiency is generally lower than that of PLR. In addition, the Neyman orthogonality of PLR gives it much stronger first-order robustness to machine learning estimation errors, enabling asymptotic normality under significantly weaker convergence rate conditions, thereby notably improving the accuracy of standard errors and confidence intervals. Therefore, PLR not only maintains the simplicity and interpretability of the model when estimating the overall average treatment effect but also takes inference efficiency into account, making parameter interpretation more intuitive. For these reasons, PLR is more suitable for estimating the overall average effect of policies as the main regression model (Chernozhukov *et al.*, 2018). Based on this, PLR was adopted as the main regression model in this paper, with IRM used for robustness testing, while PLIV and IIVM were used for endogeneity testing. The main regression model was set as follows.

$$Y_i = \theta_0 D_i + g(X_i) + U_i \tag{1}$$

$$D_i = m(X_i) + V_i \tag{2}$$

Where, Y_i is the UCE index, and D_i is the dummy variable of the ZWCP policy (taking the value 1if the city is included in the pilot program, and 0 otherwise). X_i is a potential high-dimensional control variable set; $g(X_i)$ and $m(X_i)$ are unknown functions. U_i and V_i are random perturbation terms. θ_0 is the policy effect this paper focuses on (i.e. the causal impact of ZWCP on UCE). The PLR model ensures robust estimation of θ_0 through Neyman orthogonalization and cross-fitting. The specific steps are as follows:

While fully utilizing the predictive capabilities of machine learning, it is still necessary to ensure robust inference of the main parameters. To this end, Neyman's orthogonalization idea is introduced by constructing the following "moment function":

$$\psi_i(\theta, g, m) = (D_i - m(X_i)) \left[(Y_i - g(X_i)) - \theta(D_i - m(X_i)) \right] \tag{3}$$

If $\theta = \theta_0$, and machine learning approximates $g(X_i)$, $m(X_i)$ sufficiently accurately, then:

$$E\left[\psi(\theta, g(X_i))\right] = 0 \tag{4}$$

Expanding equation (4), we get:

$$E\left[D_i - m(X_i)\right](Y_i - g(X_i)) - \theta_0 E\left[D_i - m(X_i)\right]^2 = 0 \tag{5}$$

Solving for this gives:

$$\theta_0 = \frac{E\left[D_i - m(X_i)\right]\left[Y_i - g(X_i)\right]}{E\left[D_i - m(X_i)\right]^2} \tag{6}$$

Replacing expectation operations with sample averages and using machine learning to estimate function values:

$$\hat{g}(X_i) \approx g(X_i), \hat{m}(X_i) \approx m(X_i) \tag{7}$$

The regularized estimator for θ_0 is thus:

$$\hat{\theta}_0 = \left[\frac{1}{N}\sum_{i=1}^{N}\left(D_i - \hat{m}(X_i)\right)^2\right]^{-1} \cdot \left[\frac{1}{N}\sum_{i=1}^{N}\left(D_i - \hat{m}(X_i)\right)\left(Y_i - \hat{g}(X_i)\right)\right] \tag{8}$$

Referencing Chernozhukov's research, it is emphasized that Neyman orthogonalization can only ensure that the regularized bias product term converges faster than $N^{-1/4}$ (a rate typically guaranteed by sparsity in regressions like Lasso), thereby avoiding bias from high-order estimation error product terms. However, if machine learning training and residual regression for the target parameter residual regression are performed on the same sample batch, a so-called "third term" bias (the product of prediction error terms and estimation error terms) will inevitably emerge.

Specifically, subtracting $\hat{g}(X_i)$ from both sides of equation (1), we have:

$$Y_i - \hat{g}(X_i) = \theta_0 D_i + g(X_i) - \hat{g}(X_i) + U_i \tag{9}$$

Substituting equations (2) and (9) into equation (8), we find that we can decompose

$$\frac{1}{\sqrt{N}}\sum_{i=1}^{N} V_i\left(Y_i - \hat{g}(X_i)\right) \tag{10}$$

into three parts:

a. The product of two error terms, specifically:

$$\frac{1}{\sqrt{N}}\sum_{i=1}^{N} U_i V_i \overset{P}{\sim} N\left(0, \sigma_{UV}^2\right) \tag{11}$$

b. The regularized bias product term, namely:

$$\frac{1}{\sqrt{N}}\sum_{i=1}^{N}\left(\hat{g}(X_i) - g(X_i)\right)\left(\hat{m}(X_i) - m(X_i)\right) \tag{12}$$

Even if the convergence rates of both estimation errors are relatively slow, their product in regularization will converge faster than $N^{-1/4}$, thus becoming an infinitesimal term as $N \to \infty$.

c. The product of error terms and estimation errors, specifically:

$$\frac{1}{\sqrt{N}}\sum_{i=1}^{N} V_i\left(\hat{g}(X_i) - g(X_i)\right), \quad \frac{1}{\sqrt{N}}\sum_{i=1}^{N} U_i\left(\hat{m}(X_i) - m(X_i)\right) \tag{13}$$

Assumption:

$$\hat{g}(X_i) = g(X_i) + \frac{U_i}{N^{\frac{1}{2}-\delta}} \tag{14}$$

Therefore:

$$\hat{g}(X_i) - g(X_i) = O_p\left(N^{-\frac{1}{2}+\bar{\delta}}\right) \tag{15}$$

This is a relatively fast convergence rate for an almost parametric model. Substituting this into (13), we have:

$$\frac{1}{\sqrt{N}}\sum_{i} V_i\left(\hat{g}(X_i) - g(X_i)\right) = \sqrt{N} O_p\left(N^{-\frac{1}{2}+\bar{\delta}}\right) = O_p\left(N^{\bar{\delta}}\right) \to \infty \tag{16}$$

The final result $O_p\left(N^{\bar{\delta}}\right)$ is a quantity that asymptotically diverges as the sample size N increases, which means the estimation bias does not disappear but instead continues to increase with increasing sample size. This bias primarily stems from the fact that the sample used to estimate $\hat{m}(\cdot)$ contains information that is potentially correlated with V_i, making V_i and $\hat{g}(X_i) - g(X_i)$ potentially correlated. In other words, because the same sample is used both to simultaneously participate in estimating $\hat{g}(\cdot)$ and in estimating $\hat{g}$'s θ_0, this leads to non-negligible estimation bias.

To eliminate this bias, this paper adopts a cross-fitting method. The specific steps are as follows:

(1) Randomly divide the sample into s parts: I_1, I_2, …., I_S;
(2) Estimate machine learning models *m* and *g* on the complement of the s-th sample;
(3) Calculate residuals using the s-th sample;
(4) Repeat the above steps for each sample part;
(5) Finally, take a weighted average of the estimates from each part to obtain the final $\hat{\theta}_0$.

Through this approach, the training of machine learning models and the estimation of parameters are conducted on different samples, effectively avoiding the "third term" bias problem. This method not only ensures unbiased estimation but also enhances estimation efficiency.

3.2. Variable definition

3.2.1. Dependent variable

The dependent variable in this paper is estimated urban carbon emissions (UCE). Since the scientific validity, robustness, and feasibility of using nighttime light remote sensing data for carbon emission estimation have been confirmed by numerous scholars, this study adopts the approach of X. Wang *et al.* (2024) and Wang & Guo (2026). Specifically, the PSO-BP algorithm was used to fit and train a model linking carbon emissions and nighttime lighting data, ultimately obtaining spatially consistent and temporally complete UCE data. The specific steps are as follows:

I. Data preparation

Carbon emission data and nighttime lighting (NTL) data from various provinces and municipalities were collected and organized for this research, with the total digital-number (DN) value, individual dummy variables and the year of NTL data as input parameters, and the Intergovernmental Panel on Climate Change (IPCC) carbon emission data for each province and city as output parameters. To improve data quality, the data was standardized to ensure scale consistency across different features.

II. Data segmentation

An 80%-20% data partitioning strategy was adopted to divide the dataset into a training set and a testing set, which were used for model construction and performance evaluation, respectively.

III. Initialize BP neural network and PSO algorithm parameter settings

In the construction process of the PSO-BP hybrid prediction model, the first step is to determine the topological structure of the BP neural network based on the feature dimensions and distribution characteristics of the input data. A suitable network architecture was established by analyzing the number of nodes in the input layer, hidden layer, and output layer, in order to optimize the learning ability, computational efficiency, and generalization performance of the model. Meanwhile, key parameters of the PSO algorithm were set, including the size of the particle swarm, the maximum number of iterations, learning factors *c1* and *c2*, as well as hyperparameters such as dynamic inertia weights. In the initialization phase, the position and velocity vectors of each particle in the particle swarm were randomly initialized, with the position code of each particle representing a complete and unique set of weights and threshold parameters for the BP neural network.

IV. Fitness function design

The root mean square error (RMSE) was used as the fitness function of the PSO algorithm to quantitatively evaluate the quality of the network parameter combinations represented by each particle. RMSE accurately reflects the degree of deviation between the predicted output of the network and the true target value, with smaller values indicating better network performance. By minimizing RMSE, the PSO algorithm can guide particle swarm to search in the direction of minimizing the network prediction error, thereby achieving effective optimization of BP neural network parameters.

V. Iterative optimization

In the iterative optimization phase of the PSO algorithm, the velocity and position information of each particle were dynamically and adaptively updated based on the evaluation results of the predefined fitness function. The algorithm continuously adjusted the search direction and step size of particles by tracking the individual historical optimal position and the global best position simultaneously. In each iteration, the BP neural network was initialized with updated new particle position parameters, and then trained with standard forward and backward propagation using the prepared training dataset. In this way, the PSO algorithm can perform a comprehensive global search in the parameter space, effectively avoiding the problem of the traditional BP algorithm easily becoming trapped in local optimal solutions, and improving the overall convergence speed and prediction accuracy of the network.

VI. Model training and performance evaluation

The optimal weights and threshold parameters obtained through PSO algorithm optimization were used as the initial parameters of the BP neural network, and the optimized network was further trained with the training dataset through multiple iterations. During the training, the BP algorithm performed forward and backward propagation, and the network parameters were continuously refined through gradient descent to minimize prediction errors effectively.

After training, a comprehensive performance evaluation was conducted to assess the model's effectiveness. The predictive performance and data distribution characteristics were visually demonstrated by generating a scatter plot analysis between predicted and actual values. The coefficient of determination (R^2) was employed as the core and authoritative evaluation indicator to quantitatively evaluate the explanatory power of the model for data variability and goodness-of-fit. As shown in **Figure 5**, the R^2 of the training set reached 0.934, the R^2 for the test set was 0.920, and the R^2 for the entire dataset was 0.932, indicating that the model exhibits excellent fitting ability and strong generalization ability. The data points in the scatter plot are tightly and consistently distributed near the ideal prediction line (Y=T), which further verifies the high-precision performance of the PSO-BP hybrid model in predicting UCE. These evaluation results convincingly demonstrate the reliability, applicability and practicality of the model, providing a solid technical foundation for accurate UCE forecasting and informed policy-making.

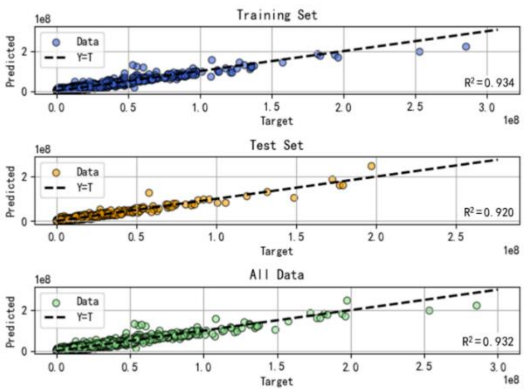


Figure 5. Performance evaluation of the PSO-BP model.

VII. UCE prediction based on urban NTL data

UCE data were obtained by converting municipal NTL data into input parameters and inputting them into a trained neural network model.

Table 2. Variable definition.

Variable	Definition
Urban carbon emissions ($lnCO_2$)	Natural logarithm of the carbon emissions obtained by the PSO-BP algorithm
Zero-waste city pilot policy (*zwcp*)	Assigned value 1 after policy implementation, 0 otherwise
Economic development level (*gdppc*)	GDP / permanent resident population
Economic growth rate (*gdpgr*)	GDP growth rate
Financial development level (*fdl*)	Year-end financial institution deposit balance / GDP
Government Intervention (*gi*)	General public budgetary revenue of local governments / GDP
Foreign Openness (*fo*)	Total imports and exports of goods / GDP
Population Density (*lnpd*)	Natural logarithm of population per square kilometer
Degree of dependence on foreign investment (*fidd*)	Actual utilized foreign investment in the year / GDP
Internet Development Level (*lnidl*)	Natural logarithm of the number of international internet users
Level of human capital (*lhc*)	Number of college students per 10,000 people / 10,000
Transportation accessibility (*lnta*)	Natural logarithm of highway passenger volume
Proportion of science and technology expenditure (*ste*)	Science expenditure / general local government budgetary expenditure
Science and technology research (*lntr*)	Natural logarithm of the number of patent applications

3.2.2. Core explanatory variable

The core policy-related explanatory variable in this paper is the Zero Waste City Pilot Policy (ZWCP). The year 2019 was set as the official policy launch year in this paper according to the first batch of "11+5" ZWCP pilot lists announced by the Chinese State Council in May 2019. The specific variable assignment method is as follows: for pilot cities, the value of ZWCP from 2019 (inclusive) onward was set to 1, and the value before 2018 was set to 0. For non-pilot cities, the value was set to 0 consistently throughout the entire sample period. This coding allows identification of whether each city was affected by the ZWCP policy and enables evaluation of the carbon reduction effect of the policy.

Table 3. Descriptive statistic.

Type	Variable	Obs	Mean	SD	Min	Max
Explained variable	$lnCO_2$	3731	16.918	0.991	13.825	19.552
Core explanatory variable	*zwcp*	3731	0.107	0.309	0.000	1.000
Control variables	*gdppc*	3731	10.729	0.597	8.576	12.456
	gdpgr	3731	8.162	4.329	-20.630	25.100
	Fdl	3731	1.520	0.774	0.371	20.100
	Gi	3731	0.076	0.028	0.023	0.240
	Fo	3731	0.200	0.341	0.000	3.659
	lnpd	3731	5.739	0.908	1.792	7.943
	fidd	3731	0.002	0.003	0.000	0.029
	lnidl	3731	13.411	1.048	9.210	17.762
	Lhc	3731	0.018	0.021	0.000	0.129
	lnta	3731	8.009	1.315	1.609	12.184
	Ste	3731	0.015	0.030	0.000	0.936
	lntr	3731	8.021	1.846	1.099	12.583

Table 4. Baseline regression result.

	$lnCO_2$	$lnCO_2$	$lnCO_2$	$lnCO_2$
	(1)	**(2)**	**(3)**	**(4)**
Zwcp	-0.121***	-0.124***	-0.117***	-0.112***
	(0.039)	(0.040)	(0.044)	(0.043)
Control (single term)	Y	Y	Y	Y
Control (quadratic term)	N	Y	Y	Y
City FE	N	N	N	Y
Year FE	N	N	Y	Y
N	3731	3731	3731	3731

Note: The dependent variable is urban carbon emissions. Column (1) includes the linear terms of the control variables. Column (2) adds the quadratic terms of the control variables. Column (3) includes year fixed effects. Column (4) includes all control variables and fixed effects. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

3.2.3. Control variables

The DML model effectively addresses the problem of the curse of dimensionality in controlling variables. Due to the many factors that affect UCE, 12 control variables potentially influencing UCE were selected by referring to the research of Byrne *et al.* (2024) to isolate the pure policy effect. These include economic development level, economic development speed, financial development level, and degree of government intervention. Following the approach of Ling *et al.* (2024), the quadratic terms of the above variables were added to improve the model fit accuracy and capture potential nonlinear relationships. Meanwhile, individual and year dummy variables were introduced to control for the fixed effects of cities and time.

The meanings of the main variables are explained in **Table 2**.

3.2.4. Data description and descriptive statistics

This study employs a panel dataset covering 287 Chinese cities from 2010 to 2022. The control variables are compiled primarily from the China City Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, China Urban Construction Statistical Yearbook, and the annual Statistical Communiqués on National Economic and Social Development. Carbon emission data is sourced from the CEADs database (https://www.ceads.net.cn/data/province/), while NTL data are obtained from Harvard Dataverse (https://dataverse.harvard.edu/). Descriptive statistics for the main variables are presented in **Table 3**.

4. Empirical analysis

4.1. Baseline estimation results

In this paper, the DoubleML package in Python and the PLR model were used to evaluate the impact of the ZWCP policy on urban carbon reduction. Compared with the DoubleML package available in Stata software, which is commonly used in academia, Python's DoubleML offers more comprehensive and flexible functions (Bach *et al.*, 2024). In the benchmark regression, a 1:4 training-to-testing sample segmentation and the random forest algorithm were used, and all other parameters were maintained at the default settings of the DoubleML package to ensure comparability of results. During the regression process, control variables—including primary terms, quadratic terms, year fixed effects, and city fixed effects—were included sequentially. The relevant regression results in **Table 4** indicate that the regression coefficients of the ZWCP policy were all negative at the 1% significance level, demonstrating that the ZWCP policy promotes urban carbon reduction.

4.2. Robustness checks

4.2.1. Cluster robust

DML achieves the required asymptotic convergence speed by keeping the score function approximately independent outside the sample through Neyman orthogonalization and cross-fitting procedures. However, if the standard cross-fitting method proposed by Chernozhukov *et al.* is used, clustering can cause correlation between the errors of training and testing samples, which undermines the premise of "independent and identically distributed" errors. In addition, traditional variance estimation must be replaced with a cluster-robust form; otherwise, the statistical significance will be systematically exaggerated. To effectively solve this problem, all cities and years were randomly grouped in two- dimensional structure following the approach of Chiang *et al.* (2021). In the subsequent iterations, only one "city group x year group" grid was designated as S in each iteration, and the remaining grids were designated as N, ensuring that S and N were completely separated in both city and year dimensions. This approach overcomes the sample correlation problem caused by standard cross-fitting procedures and ultimately obtains the robust, clustered-adjusted standard error $\hat{\sigma}$ ultimately.

$$\hat{\sigma} = \sqrt{\hat{J}^{-1}\hat{\Gamma}\hat{J}^{-1}} \tag{17}$$

$$\hat{\Gamma} = \frac{1}{K^2}\sum_{(k,\ell)\in[K]^2}\left[\frac{|I_k|\wedge|J_\ell|}{\left(|I_k||J_\ell|\right)^2}\left(\sum_{i\in I_k}\sum_{j\in J_\ell}\sum_{j'\in J_\ell}\psi\left(W_{ij};\tilde{\theta},\hat{\eta}_{k\ell}\right)\psi\left(W_{ij'};\tilde{\theta}_0,\hat{\eta}_{k\ell}\right)+\sum_{i\in I_k}\sum_{i'\in I_k}\sum_{j\in J_\ell}\psi\left(W_{ij};\tilde{\theta},\hat{\eta}_{k\ell}\right)\psi\left(W_{i'j};\tilde{\theta}_0,\hat{\eta}_{k\ell}\right)\right)\right] \tag{18}$$

$$\hat{J} = \frac{1}{K^2}\sum_{(k,\ell)\in[K]^2}\frac{1}{|I_k||J_\ell|}\sum_{i\in I_k}\sum_{j\in J_\ell}\psi_a\left(W_{ij};\tilde{\theta}_0,\hat{\eta}_{k\ell}\right) \tag{19}$$

I_k denotes the number of clusters in the k-th fold for the first cluster variable. J_ℓ denotes the number of clusters in the ℓ-th fold for the second cluster variable. $\hat{\eta}_{k\ell}$ is an estimate of the interference function related to sample W_{ij}, which comes from observations that were not in subsets I_k and J_ℓ. The policy effect of interest (i.e. the causal impact of ZWCP on UCE) that this paper focuses on was $\hat{\theta}_0$. $\psi(\cdot)$ is an orthogonal scoring function. *K* is the number of folds of cross-fitting.

The regression results are shown in column 1 of **Table 5**. The bidirectional clustering DML estimation shows that the coefficient of the impact of policy variable ZWCP on carbon emissions was statistically and economically significantly negative, which is consistent with the baseline panel regression results. It can be seen that ZWCP still significantly reduces carbon emissions even under the most conservative bidirectional clustering DML estimation. Therefore, the main conclusion is robust and reliable.

4.2.2. Add new fixed effects

This paper adopts a more rigorous identification strategy considering the common characteristics of policy homogeneity, geographical proximity, and industrial correlation that may exist between cities within the same province. Specifically, in addition to controlling for urban fixed effects and time fixed effects, the interaction term between province dummy variables and years was further included to capture the heterogeneous trends of each province over time. This setting helps to exclude the potential impact of unobservable provincial-level factors on the estimation results. The regression results in column 2 of **Table 5** indicate that after additing the above control variables, the estimated coefficients of the key explanatory variables remained significantly negative, verifying the reliability of the main conclusions.

4.2.3. Adjust the research sample

Given the substantial significant differences in key characteristics such as economic development level, population size, and industrial structure between municipalities directly under the central government and other prefecture-level cities, including all prefecture-level and above cities in the same regression framework may lead to potential estimation bias, thus affecting the accuracy and credibility of the assessment of the overall carbon emission reduction effect of the ZWCP policy. Based on relevant research practices, Beijing, Tianjin, Shanghai, and Chongqing—which are the four municipalities directly under the central government, were excluded from the sample for focused regression analysis in order to ensure the robustness and reliability of the research conclusions. The estimated results in column 3 of **Table 5** show that the impact coefficient of the ZWCP policy remained consistently significantly negative on carbon emission reduction after carefully adjusting the sample range, indicating that the policy played a positive role in promoting carbon emission reduction. This finding further confirms the robustness of the benchmark regression results.

4.2.4. Elimination of outliers

Outliers in the research sample may bias the evaluation results of the carbon reduction effect of the ZWCP policy. To ensure the accuracy and robustness of the policy effect estimation, winsorization was performed on the control variables—excluding policy variables—within the benchmark regression at the 1% and 99% quantiles, and the 5% and 95% quantiles, respectively. Extreme values beyond these specified quantile ranges were replaced with their corresponding quantile values for subsequent regression analyses. The results are shown in columns 4 and 5 of **Table 5**. The regression coefficients of the ZWCP policy maintained significantly negative characteristics under both winsorization schemes, indicating that the policy can effectively promote the reduction of carbon emissions. This finding further confirms the reliability of the benchmark regression results.

Table 5. Robustness check I.

	Cluster robust	**Province - time trends**	**Delete center city**	**1%**	**5%**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
zwcp	-0.220*	-0.108***	-0.112***	-0.122***	-0.103**
	(0.053)	(0.042)	(0.043)	(0.043)	(0.040)
Control (single term)	Y	Y	Y	Y	Y
Control (quadratic term)	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N	3731	3731	3731	3731	3731

*Notes: The dependent variable is urban carbon emissions. Column (1) reports results from the cluster-robust double machine learning model. Column (2) adds new fixed effects. Column (3) adjusts the research sample. Columns (4) and (5) apply two-sided winsorization at the 1% and 5% levels for continuous variables, respectively. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 6. Robustness check II.

	IRM	**Kfolds=3**	**Kfolds=8**	**Lassocv**	**XGBoost**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
zwcp	-0.117***	-0.123***	-0.110**	--0.168***	-0.136***
	(0.025)	(0.044)	(0.043)	(0.050)	(0.044)
Control (single term)	Y	Y	Y	Y	Y
Control (quadratic term)	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N	3731	3731	3731	3731	3731

*Note: The dependent variable is urban carbon emissions. Column (1) uses an interactive model. Columns (2) and (3) change the sample split ratio. Columns (4) and (5) use lasso regression and extreme gradient boosting for prediction, respectively. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

4.2.5. Reset the DML model

To avoid the influence of potentially biased settings in DML on research conclusions, the robustness of the benchmark regression results was verified from the following key aspects: (1) Changing the model specification. The PLR model was used for initial benchmark regression, and IRM was used for additional robustness testing to further confirm the validity of the conclusions. Moreover, propensity scores close to the boundary were carefully pruned, with a pruning threshold set at 0.01, in order to reduce the influence of disproportionately extreme propensity score weights in the interaction model. (2) Adjusting the sample segmentation ratio. The sample segmentation ratio in benchmark regression was adjusted from 1:4 to both 1:2 and 1:7 to examine the sensitivity and stability impact of different segmentation ratios on research conclusions. (3) Changing machine learning algorithms. The prediction algorithm in the DML model was changed from the random forest to Lasso regression and extreme gradient boosting, in order to explore the robustness impact of different machine learning algorithms on research conclusions.

Columns (1) to (5) of **Table 6** show the regression results after the DML model was reset. Obviously, neither the model specification, sample segmentation ratio, nor machine learning algorithms used for prediction change the conclusion that the ZWCP policy reduces carbon emissions, but only affect the policy effect to a certain extent. It further proves the robustness of the benchmark regression.

4.2.6. Instrumental variable

Pilot areas for zero-waste cities are randomly selected to some extent, which may introduce endogeneity issues due to the influences from resource endowment factors such as economic development level, degree of informatization, and industrial structure. Based on this, this paper adopts a PLIV model, drawing on the research method of Shen *et al.* (2024). Specifically, improvements were made based on the research of B. Guo *et al.* (2025) by selecting the interaction term between regional average slope and river density as the instrumental variable for the policy of zero-waste cities. From a causal correlation perspective, these instrumental variable influences policy implementation through two main channels. Firstly, the construction of zero-waste cities requires significantly improving the efficiency of garbage treatment, and the terrain slope is positively correlated with the overall cost of garbage treatment. Research shows that steep slope areas require special transportation equipment such as cable cars, and mountainous terrain requires costly and complex additional slope stabilization measures. In addition, garbage collection vehicles in hilly areas have higher fuel consumption, and the cost of leachate treatment in mountainous landfills is much higher than that on flat land. These factors are therefore closely related to the operational efficiency of constructing a zero-waste city. Secondly, river density affects policy implementation by influencing the degree of urban solid waste pollution. Cities with high river density often have convenient transportation conditions. This locational advantage is more attractive for companies to invest in building factories. This tends to increase solid waste pollution, prompting local governments to strengthen the implementation of solid waste management policies. From an exclusivity perspective, regional average slope and river density, as natural geographical features, are exogenous variables not directly correlated with urban carbon reduction. Therefore, the natural logarithm of the interaction term between these two indicators as an instrumental variable satisfies the requirements of relevance and exogeneity of instrumental variables in econometrics.

Table 7. Robustness check III.

	PLIV	**IIVM**
	(1)	**(2)**
Zwcp	-0.126*	-0.118**
	(0.054)	(0.033)
Control (single term)	Y	Y
Control (quadratic term)	Y	Y
City FE	Y	Y
Year FE	Y	Y
N	3731	3731

*Note: The dependent variable is urban carbon emissions. Column (1) presents a partially linear regression model with instrumental variables, and column (2) presents an interactive model with instrumental variables. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 8. Sensitivity analysis.

	CI lower	**Theta lower**	**Theta**	**Theta upper**	**CI upper**	**RV**
	(1)	(2)	(3)	(4)	(5)	(6)
zwcp	-0.213	-0.202	-0.112	-0.021	-0.011	4.259%

Note: "CI lower" and "CI upper" respectively represent the lower and upper limits of the adjusted confidence intervals for the treatment effect in the context of unobserved confounding factors. "Theta lower" and "Theta upper" are the lower and upper bounds for adjusting the bias of point estimates under the set sensitivity parameters, without considering sampling fluctuations. The "Theta" column represents the point estimate itself after correction by sensitivity analysis. RV is used to measure the strength of the unobserved confounding variables required to make the results no longer significant.

Column 1 of **Table 7** shows that the estimated coefficients of policy variables are significantly negative, consistent with the baseline regression results. Furthermore, the IIVM was employed to verify the robustness of the results.

Column 2 of **Table 7** indicates that the estimated coefficients of policy variables remain strongly significantly negative, confirming that the model has successfully passed the rigorous endogeneity test.

4.2.7. Sensitivity analysis

A sensitivity analysis method was carefully emploeyd in this paper to test the potential impact of hidden unobserved confounding factors on the research conclusions, aiming to further verify the reliability of the estimated carbon reduction effect estimation of the ZWCP policy. Although DML can alleviate the problem of omitted variable bias to some extent, there may still be complex confounding factors that are difficult to observe or quantify in the policy evaluation process, such as the environmental awareness of company decision-makers, implicit policy implementation differences among local governments, and informal cooperation networks between regions. These unobserved factors may simultaneously affect the intensity of policy implementation and the effect of the carbon reduction effect, leading to systematic bias in the estimation of causal effects. In this paper, based on the latest research by Chernozhukov *et al.* (2022), the sensitivity analysis method for DML was used to evaluate whether the findings are influenced by unobserved confounding factors. Based on the research of Facure & Germano (2021), the sensitivity analysis function from the DoubleML package was applied to ensure the reliability of the results. The sensitivity analysis is based on three parameters the strength and correlation of confounding: cf_y and cf_d and the parameter rho. cf_y measures the proportion of residual variance in the outcome explained by unobserved confounders; cf_d measires the porportion of residual variance in the treatment representation explained by unobserved confounders ; rho measures the correlation between the difference of the long and short forms of the outcome regression and the Riesz representer. Regarding parameter settings, Chernozhukov *et al.* argue that confounding should not account for more than 4% of the residual variation of the outcome and 3% of the residual variation of the treatment. They also argue that the default value of rho being 1.0 is conservative and accounts for adversarial confounding. Therefore, in this paper, we set $cf_y = 0.04$, $cf_d = 0.03$, and $rho = 1.0$.

The sensitivity analysis results are shown in **Table 8**. The confidence intervals for estimating the policy effect maintain significant negative characteristics under the specified mixed intensity parameters, indicating that the carbon emission reduction effect of the ZWCP policy remains significant even under a high level of confounding. The RV was 4.259%, which means that unobserved confounding factors would need to simultaneously explain at least 4.259% of the residual variation in both the treatment and outcome variables in order to render the carbon reduction effect of the ZWCP policy statistically insignificant. The contour plot (**Figure 6**) further illustrates the effect contour corresponding to different levels of confounding intensity, where the confounded scenario is labeled "Scenario" and the unconfounded case is labeled "Unadjusted." At higher levels of confounding, the upper bound of the ZWCP policy's effect contour remains negative at the 95% confidence level. Therefore, this research passed the sensitivity test, and the conclusion that the ZWCP policy promotes carbon reduction is robust, providing reliable empirical evidence for evaluating policy effects.

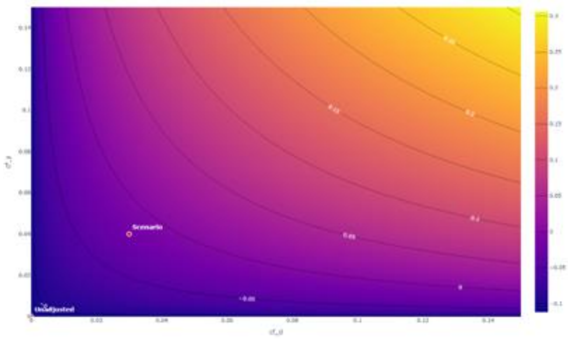


Figure 6. Contour plot of the sensitivity analysis.

5. Heterogeneity test

Double machine learning provides a flexible framework for examining heterogeneous treatment effects in the presence of complex confounding and nonlinear relationships. This enables us to gain a deeper understanding of the varied reactions of different individuals or groups under specific policies or interventions, thereby achieving more targeted and effective precise policy-making and implementation. In this paper, based on the research of Knaus (2022) and Kallus *et al.* (2019), the Group Average Treatment Effect (GATE) and Conditional Average Treatment Effect (CATE) methods in the DoubleML package were used to discuss the heterogeneity across different city types and urban characteristics, respectively.

5.1. Heterogeneity of city types

To deeply analyze the heterogeneous impact of the ZWCP policy on UCE, this paper conducted detailed research on various city types. Firstly, based on the stringency and intensity of environmental supervision, cities were divided into major eco-friendly cities and non-major eco-friendly cities, according to the list of major eco-friendly cities in the authoritative China Environmental Yearbook. Secondly, based on the degree of resource abundance, cities were classified as resource-based and non-resource-based cities according to the official National Sustainable Development Plan for Resource-Based Cities (2013-2020) issued by the State Council of China on November 12. Thirdly, based on the foundation of industrial development, cities were categorized as old industrial bases and non-old industrial bases, according to the National Plan for the Adjustment and Transformation of Old Industrial Bases (2013-2022) approved by the China Development and Reform Commission in early March 2014.

The grouped regression results based on environmental regulation intensity in **Table 9** show that the ZWCP policy has a significant negative effect on carbon emissions in major eco-friendly cities, but its effect is not significant in non-major eco-friendly cities. The possible reasons for the significant difference between the two groups are as follows. Major eco-friendly cities have a more diversified economic structure and a relatively high proportion of service and high-tech industries, which have lower carbon emission intensity compared with heavy or resource-based industries. Thus, these cities can better leverage the positive effects of policies and achieve significant emission reduction targets after implementing the ZWCP policy. In contrast, non-major eco-friendly cities may have deficiencies in environmental management and the implementation of environmental policies, which can weaken the effectiveness of the ZWCP policy. These cities may rely on heavy and traditional industries, face considerable carbon emission pressure, and lack advanced infrastructure and technology. As a result, they may respond more slowly to environmental policies, making it difficult to achieve significant reductions in carbon emissions.

The grouped regression results of resource abundance in **Table 9** show that the ZWCP policy has a significant negative effect on carbon emissions in non-resource-based cities, while the effect is not significant in resource-based cities. Several economic and institutional mechanisms may underline the observed differences between these two groups. According to the grouped regression results of resource abundance shown in **Table 9** show that the ZWCP policy has a significant negative effect on carbon emissions in non-resource-based cities, while the effect is not significant in resource-based cities. Non-resource-based cities generally rely heavily on service and high-tech industries, with relatively low energy consumption and carbon emissions, which makes it easier for these cities to achieve effective reductions in carbon emissions through policy guidance during the implementation of the ZWCP policy. In addition, they have strong adaptability to adjustments in industrial structure and the application of green technologies, which enables them to respond quickly to policy requirements, thereby exerting a stronger policy effect. In contrast, resource-based cities rely heavily on traditional heavy industry and resource extraction, and their economic models are highly dependent on fossil fuels. These cities face a high baseline of carbon emissions, making it difficult to observe immediate policy effects due to the substantial investments required for transformation. In addition, resource-based cities tend to respond more slowly to policy incentives, hindered by insufficient technological foundations and market mechanisms to effectively support policy goals, which hinders the achievement of emission reduction effects.

The grouped regression results of the industrial development foundation in **Table 9** show that the pilot cities in both old industrial bases and non-old industrial bases have a statistically significant and meaningful effect on carbon emission reduction, but the latter show greater statistical significance. The reason for this difference may be that old industrial bases have comparative strengths in policy support, technological investment, and transformation and upgrading. Due to their historical reliance on heavy industry, these cities often encounter substantial challenges but are able to take timely and effective measures more quickly when implementing carbon reduction technologies. In addition, local governments' enthusiasm for environmental policies and the promotion of green technologies help these areas to implement emission reduction strategies more effectively. However, old industrial bases also face certain persistent challenges, including the slow adjustment of their industrial structure and delayed technological upgrades. Despite their significant emission reduction effects, it is necessary to pay attention to the potential environmental and economic risks in these areas during the transformation in order to achieve sustainable development. Therefore, during policy formulation, it is necessary to take into account the unique actual situation of old industrial bases, promote the green transformation of industries, and enhance their competitiveness in emerging green industries, so as to more comprehensively promote the achievement of the national carbon reduction targets.

Table 9. Group Average Treatment Effect.

	Geographical location		Resource endowment		Industrial Development	
	Key	Non-Key	Affluence	Lack	Old	Non-Old
	(1)	(2)	(3)	(4)	(5)	(6)
Policy	-0.150**	-0.093	-0.083	-0.145***	-0.152**	-0.104*
	(0.061)	(0.064)	(0.074)	(0.054)	(0.076)	(0.053)
Control (single term)	Y	Y	Y	Y	Y	Y
Control (quadratic term)	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	1417	2314	1661	2275	1209	2522

*Note: The dependent variable is urban carbon emissions. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

5.2. Heterogeneity of city characteristics

Figure 7 shows the ranking results of the importance of control variables obtained using the random forest model. The two variables that contributed most significantly to the carbon reduction effect in the construction of zero-waste cities were Science and Technology Research and

Internet Development Level, with importance values exceeding 5%. Therefore, it is necessary to explore how these two urban characteristics influence the carbon reduction effect of zero-waste city construction. Accordingly, this paper conducts a heterogeneity analysis based on science and technology research and internet development level.

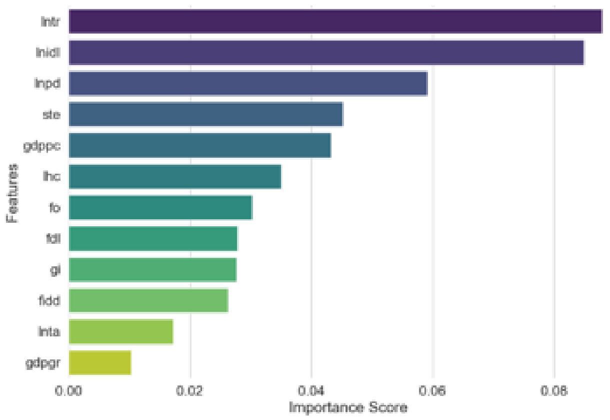


Figure 7. Feature importance ranking plot based on random forest.

The heterogeneous treatment effect of science and technology research in different areas is shown in **Figure 8**. In areas with relatively lower levels of science and technology research, the regression results of the ZWCP policy were positive, and the carbon emission reduction effect was relatively weak. This indicates that the policy has some emission reduction effect under certain basic and limited conditions, but this effect may not be further enhanced due to the lack of efficient technological support and innovative capabilities. However, the carbon reduction effect of this policy begins to show a markedly significant impact once the level of science and technology research reaches a certain threshold. This change may be closely related to the substantial improvement of technological applications and the optimization of resource management efficiency. With technological advancement, the extensive application of green technology can more effectively enable waste recycling and reduce greenhouse gas emissions, thus making the zero-waste city strategy yield more significant emission reductions. Hence, the improvement of science and technology research is crucial for achieving the expected emission reduction effect of the ZWCP policy. Policymakers should pay attention to increased investment in science and technology research, promote technological innovation, and maximize the potential of ZWCP policies, thereby promoting the achievement of broader and long term carbon reduction objectives.

The heterogeneous treatment effect of Internet development levels in different areas is shown in **Figure 9**. The carbon emission reduction effect of the pilot policy for zero-waste cities is positive in areas with low Internet development, but still relatively limited. This is because, in these areas, the lower public environmental awareness and participation in environmental protection, along with insufficient promotion and implementation of environmental measures, result in the inability to fully demonstrate the effectiveness of the overall policy. However, the situation changes significantly with the improvement of Internet development. The carbon emission reduction effect of zero-waste cities begins to take a significant effect immediately once the level of Internet development reaches a certain threshold. This is mainly because Internet development has improved the public awareness of environmental protection and broadened their understanding of the importance of sustainable development and waste management. The convenience of information dissemination has significantly raised society's attention to environmental policies and encouraged more residents to actively participate in the construction of zero-waste cities. Furthermore, the rapid advancement of Internet technology greatly facilitates information sharing and the development of green business models. For example, activities such as waste recycling and reuse through online platforms help improve the efficiency of resource utilization. These factors work together to dramatically strengthen carbon emission reduction in areas with developed Internet. Therefore, when implementing the zero-waste city strategy, policymakers should attach importance to the development and application of the Internet, with a view to further enhancing the public's environmental awareness and maximizing the policy's potential for emission reduction with the help of digital tools and information-sharing mechanisms.

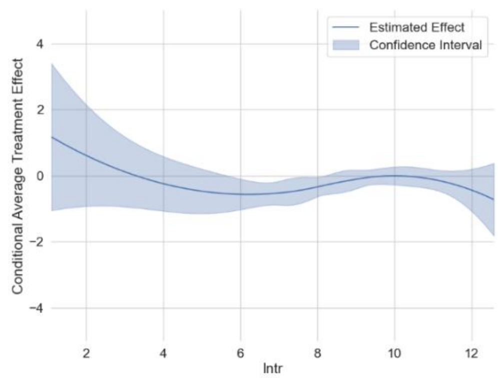


Figure 8. CATE of Science and technology research.

6. Conclusions, policy recommendations and limitations

6.1. Conclusions

The pilot policy of zero-waste cities is an important tool to promote source reduction and resource utilization of urban solid waste, and achieve the transformation toward a green urban development model. It is also a key lever to help China achieve its “dual carbon” goals and build a circular society. Based on panel data from 287 cities in China from 2010 to 2022, this paper employs DML to explore the impact of zero-waste city construction on UCE and its heterogeneous effects. The empirical results indicate that: (1) the implementation of the ZWCP policy has a significant inhibitory effect on carbon emissions in pilot areas. These conclusions remain valid after the adjustment of the research sample, resetting the DML model, conducting sensitivity analysis, and performing a series of robustness tests. (2) The construction of zero-waste cities has a more significant carbon reduction effect in major eco-friendly cities, non-resource-based cities, and old industrial base cities compared to non-major eco-friendly cities, resource-based cities, and non-old industrial base cities. (3) Improvements in technology research and development levels and Internet development generally enhance the carbon emission reduction effect of zero-waste cities.

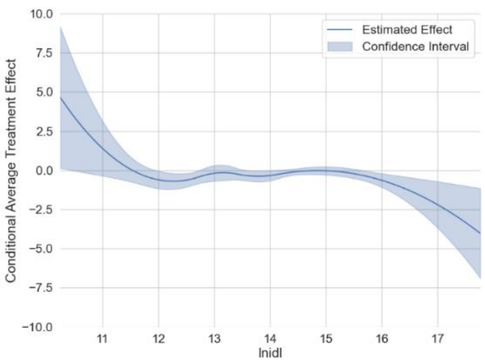


Figure 9. CATE of internet development level.

6.2. Policy recommendations

Firstly, deepen the connotation of constructing zero-waste cities and scientifically and orderly expand the scope of pilot projects. The pilot city government should adhere to the concept of “solid waste industry collaboration,” strengthen the monitoring and evaluation of solid waste’s entire life-cycle carbon emissions in the pilot areas of zero-waste cities, incorporate carbon reduction targets into the indicator framework of zero-waste city construction, and guide companies and residents to practice a “simple, moderate, green, low-carbon, and healthy” lifestyle and consumption pattern.” On the basis of meeting the current requirements for being declared to be a zero-waste city, the government should strengthen the assessment standards for “source reduction, comprehensive resource utilization, and safe disposal,” make synergistic carbon reduction and efficiency gains a core criterion for selecting pilot cities, consider factors such as development levels and industrial characteristics of different regions, and prioritize the cities with a strong circular economy foundation and solid waste treatment capabilities. Moreover, the government should follow a phased development approach, promptly summarize the carbon reduction experiences of pilot cities in building the four major guarantee systems of “institutional, market, technological, and regulatory,” form a demonstrable and scalable model for zero-waste city construction. This will help gradually realize the transformation from “perceived zero-waste” to “circular zero-waste,” and support the building of a circular “zero-waste society” that contributes to achieving the “dual carbon” goals.

Secondly, promote the construction of zero-waste cities according to local conditions and implement targeted measures to enhance carbon reduction efficiency. In response to the heterogeneous carbon emission reduction effects in major eco-friendly cities, non-resource-based cities, and old industrial base cities in the construction of zero-waste cities, the government should adhere to the basic principles of adapting measures to local conditions and focusing on differentiated policies, identify the weak points and key links in the generation, collection, transfer, utilization, and treatment of major solid waste according to the characteristics of regional industrial structure, development stage, and other relevant factors. For major eco-friendly cities, it is necessary to fully leverage their pioneering leading role in institutional innovation and technological demonstration, and accelerate the systematic construction of the four core guarantee systems: institutional system, market system, technological system, and regulatory system. For old industrial base cities, it is necessary to coordinate balanced and sustainable urban development and solid waste management, optimize industrial structure layout, and build a phased utilization and recycling system of resources and energy between industry, agriculture and residential sectors. For non-resource-based cities, it is necessary to strengthen the development concept of “source reduction, full utilization of resources, and safe treatment,” and promote the realization of green and circular production, distribution, and consumption in all relevant aspects.

Thirdly, strengthen technological innovation and digital empowerment, and build a smart zero-waste city development system. In view of the fact that the improvement of science and technology research and internet development level can enhance the carbon emission reduction effect of zero-waste cities, the government should further increase investment in research and development of key technologies and equipment for solid waste recycling, cultivate a number of leading companies for solid waste recycling, and establish a comprehensive solid waste big-data-driven intelligent environmental protection monitoring platform to achieve more precise supervision of the entire chain of urban solid waste generation, collection, transfer, utilization and treatment. Meanwhile, it should make full use of Internet technologies to promote the “integration of digital and physical networks,” establish the industrial chain of renewable resources, promote the recycling of renewable resources, and enhance the circular utilization of urban mines and resources. It should also achieve synergistic carbon reduction and efficiency improvement by deeply integrating digital technologies with the construction of zero-waste cities and constructing a circular economy industry chain based on material flow analysis, thus realizing the “dual carbon” goal.

6.3. Limitations

There are some notable limitations that need to be clarified. Firstly, in this paper, empirical analysis was conducted using aggregated city-level data, providing valuable macro perspectives. However, this approach may overlook the significant behavioral differences between companies and the important role of household consumption in carbon emissions. Future research could be conducted to further explore the heterogeneous impact of this policy among different entities through more detailed survey data at the company or household level. Secondly, due to the limited availability of data, this paper does not include some potential influencing factors, such as urban residents' environmental awareness and international carbon market dynamics, in the constructed control variable system. The main analysis covers key variables such as the economy and environment, so the omission of the above content has a limited substantive impact on the overall conclusion. However, the variable dimensions could be further expanded to enrich the broader research perspective if data conditions allow in future studies. Thirdly, the increasing diversification of environmental regulation types may generate significant synergistic effects in achieving sustainable and long-term carbon reduction. This paper mainly focuses on the direct impact of pilot policies for zero-waste cities on UCE, without comparing and analyzing other related environmental policies (such as carbon emissions trading, green finance, etc.) nor examining the potential complex interaction between these policies in depth. In the future, researchers may systematically combine different environmental policies to compare their overall and combined comprehensive impact on carbon emissions, or further explore the underlying mechanism of multi-policy synergy, in order to more comprehensively evaluate their overall effect in promoting urban low-carbon transformation.

Data Availability Statement

The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

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