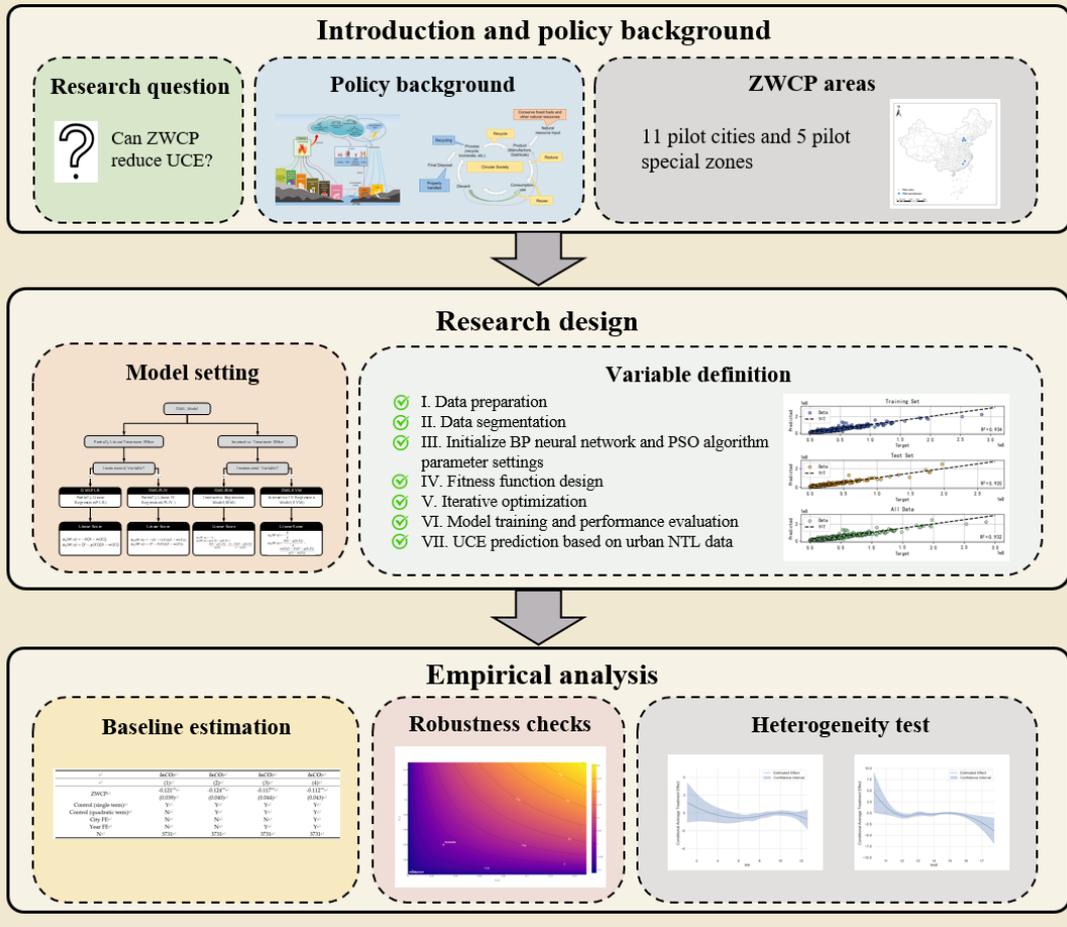






# The impact of zero-waste city pilot policies on urban carbon reduction



29

30

## Graphical abstract

31

### 1. Introduction

32

33 Over the past two decades, global resource consumption and environmental pressures have  
 34 intensified, accompanied by increasingly pronounced ecosystem degradation (Schmidt & Laner,  
 35 2025). In 2023, the global average temperature rose by approximately 1.45°C above pre-industrial  
 36 levels, accompanied by a rise in the frequency of extreme heat events (Goren et al., 2023).  
 37 According to a United Nations report, humans generate over 1 million kilograms of urban solid  
 38 waste every minute, and the accumulation of plastics, construction debris, and food waste  
 39 exacerbates land and ocean pollution (Starczewska et al., 2024). Reducing greenhouse gas emissions,  
 40 primarily carbon dioxide, has become a central policy priority for mitigating this crisis and  
 41 advancing sustainable development (Wu et al., 2016). In this context, the concept of “zero-waste  
 42 cities”, which emphasizes resource recycling and waste reduction at the source, offers a systematic

43 pathway for carbon reduction at the urban level (H. Wang et al., 2025). The General Office of the  
44 State Council issued the the Zero-Waste City Pilot (ZWCP) Work Plan in December 2018, aiming  
45 to alleviate the ecological pressures caused by solid waste through green development models. The  
46 Ministry of Ecology and Environment first announced a list of 11 pilot “zero-waste cities” in 2019  
47 and expended the list during the 14th Five-Year Plan period in 2022 to include additional cities,  
48 thereby broadening the scope of the pilot program (Qian et al., 2025). However, as an important  
49 institutional innovation to address excessive resource consumption and ecological degradation, the  
50 carbon reduction effect of the zero-waste city pilot policy has not yet been sufficiently examined  
51 using rigorous causal inference approaches. Accordingly, a rigorous identification and evaluation of  
52 its carbon reduction effects are crucial for validating policy effectiveness and optimizing low-carbon  
53 governance strategies.

54 Urban carbon emissions (UCE) are not only a key environmental indicator for measuring the  
55 severity of the climate crisis, but also a crucial metric to assess the quality of economic development  
56 and the level of ecological civilization (Bai et al., 2023). The academic community has conducted  
57 multidimensional and cross-disciplinary empirical research on the governance paths of carbon  
58 emissions, particularly focusing on the emission reduction effects of various policy tools. Using the  
59 low-carbon city pilot as a quasi-natural experiment, Yu and Zhang (2021) demonstrate that the  
60 policy significantly improves urban carbon emission efficiency, thus inhibiting carbon emission  
61 growth. C. Li et al. (2022) found that the National Emissions Trading System (ETS) indirectly  
62 suppresses the expansion of UCE by enhancing green total factor productivity. Zhang et al. (2023)  
63 verified that the green finance reform and innovation pilot zone effectively reduces both industrial  
64 energy consumption and carbon emissions through green technology innovation and capital flow  
65 adjustment. Du et al. (2023), in their study of the Energy Quota Trading (EQT) pilot, highlighted  
66 that the system not only alleviates energy mismatches and incentivizes green innovation, but also  
67 continuously improves carbon emission efficiency three years after implementation. Jiang & Sun  
68 (2024) demonstrated, using a dual machine learning model, that the construction of smart cities  
69 significantly promotes urban green development through industrial upgrading, resource  
70 optimization, and technological innovation, thereby achieving a synergistic effect on carbon  
71 emission reduction. With the Healthy City pilot as a quasi-natural experiment, Z. Guo & Zhang  
72 (2023) found that the policy reduced per capita CO<sub>2</sub> emissions by approximately 8.8%, significantly

73 improving air quality by reducing industrial emissions and enhancing public green infrastructure.

74 The ZWCP programme is a key driver for achieving the goals related to reducing solid waste  
75 at the source, promoting waste recycling, and enabling synergistic carbon reduction. Existing studies  
76 have examined the implementation effects of the ZWCP policy from multiple perspectives, yielding  
77 a range of informative empirical findings. Using 278 prefecture-level cities as samples, Bi et al.  
78 (2024) found that pilot projects significantly boosted green technology innovation through DID and  
79 causal forest methods, yielding positive outcomes via increased research and development  
80 investment and information technology upgrades. Q. Chen et al. (2025) constructed a “Five-  
81 Dimensional Multi-Index” classification framework to systematically review the governance  
82 practices of the first 16 pilot cities, providing operational indicators for horizontal comparison and  
83 policy evaluation. Y. Li & Li (2023) proposed an approach to transforming “construction indicators  
84 into evaluation indicators” and employed an obstacle degree model to identify management  
85 shortcomings, enriching the methods for pilot evaluation. Liu et al. (2024) further verified that the  
86 pilot policy significantly accelerates urban green and low-carbon transformation by incentivizing  
87 green innovation and generates positive spatial spillover effects on surrounding areas. Zhan et al.  
88 (2023) calculated the full lifecycle carbon footprint of typical zero-waste technologies through  
89 lifecycle analysis. Based on the material flow and emission coefficient method, Tian et al. (2025)  
90 estimated the overall reduction of CO<sub>2</sub> emissions from pilot projects, providing preliminary  
91 quantitative evidence for the policy's climate benefits.

92 However, most studies that evaluate UCE of the ZWCP rely on alternative metrics or simple  
93 regression tests; to date, no work has systematically embedded the policy within a causal-inference  
94 framework capable of isolating its true effect. The absence of rigorous causal identification not only  
95 weakens the credibility of policy extrapolation but also deprives subsequent mechanism studies of  
96 a solid empirical foundation. Measuring carbon emissions is inherently complex: beyond fuel  
97 consumption, it must integrate information on industrial structure, technological progress,  
98 population density and economic growth. When a large set of potential confounders must be  
99 controlled simultaneously, conventional econometric techniques are prone to the “curse of  
100 dimensionality”, wherein estimators fail to converge once the number of control variables exceeds  
101 the logarithmic order of the sample size. In addition, relationships among variables may be nonlinear,  
102 whereas standard causal models typically assume linearity, limiting their applicability. Double

103 machine learning (DML) offers a robust remedy. In its first stage, DML leverages flexible machine-  
104 learning algorithms to model and select high-dimensional covariates; through sample splitting and  
105 cross-fitting, it offsets the influence of prediction error on the causal parameter of interest, thereby  
106 preserving consistency and  $\sqrt{n}$ -rate convergence even in the presence of many controls. Accurately  
107 identifying the carbon-abatement effect of ZWCP will not only delineate the policy's net impact  
108 with greater precision but also provide the methodological bedrock for uncovering the underlying  
109 reduction, recycling and substitution pathways.

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

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

## 131 **2. Policy Background**

132 Sustained socio-economic development has led to an increase in the amount of solid waste;

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

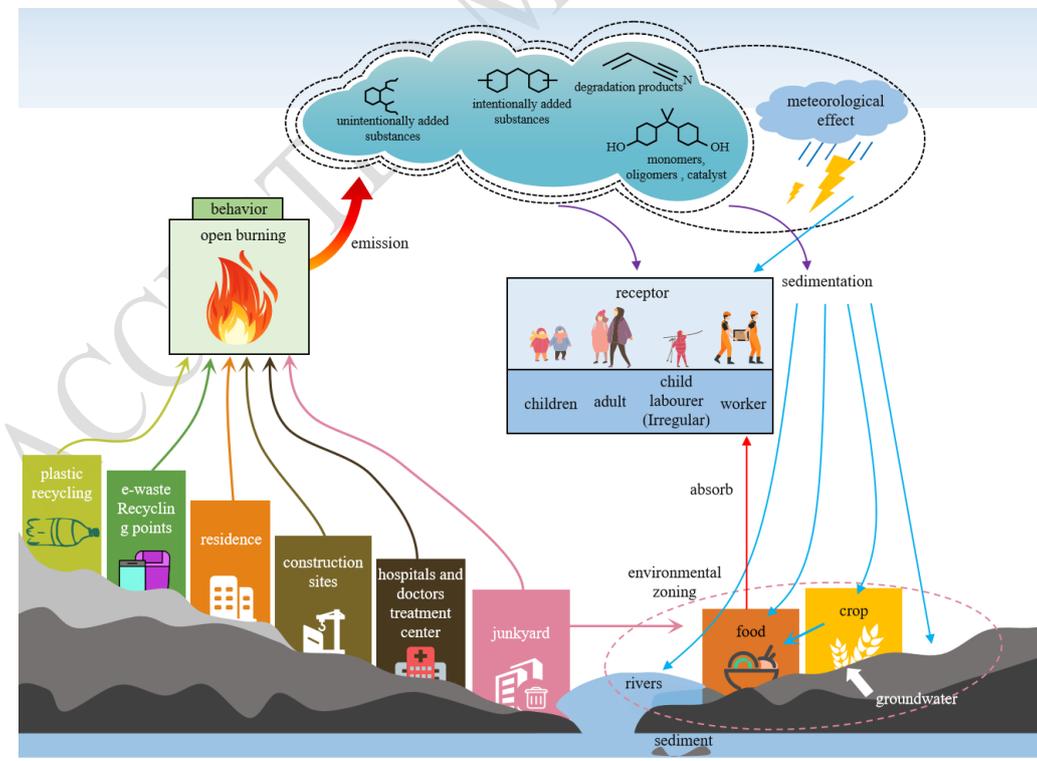


Fig. 1. Environmental impacts of uncontrolled incineration of solid waste.

150 With the continuous deepening of the concept of sustainable development, “zero-waste” has

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

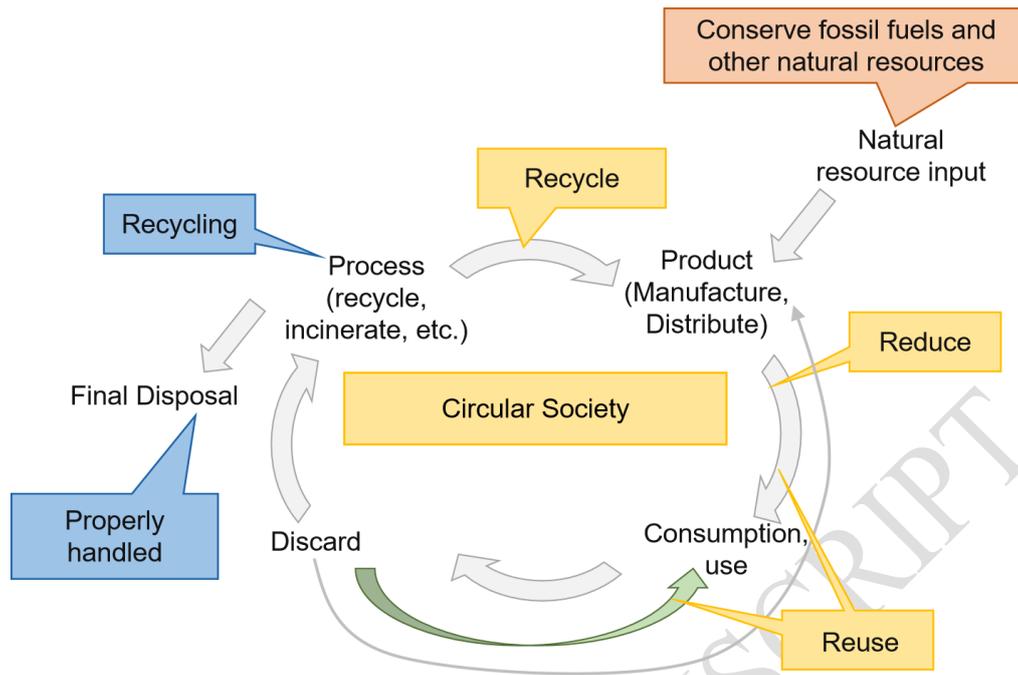


Fig. 2. Impacts of uncontrolled solid waste incineration.

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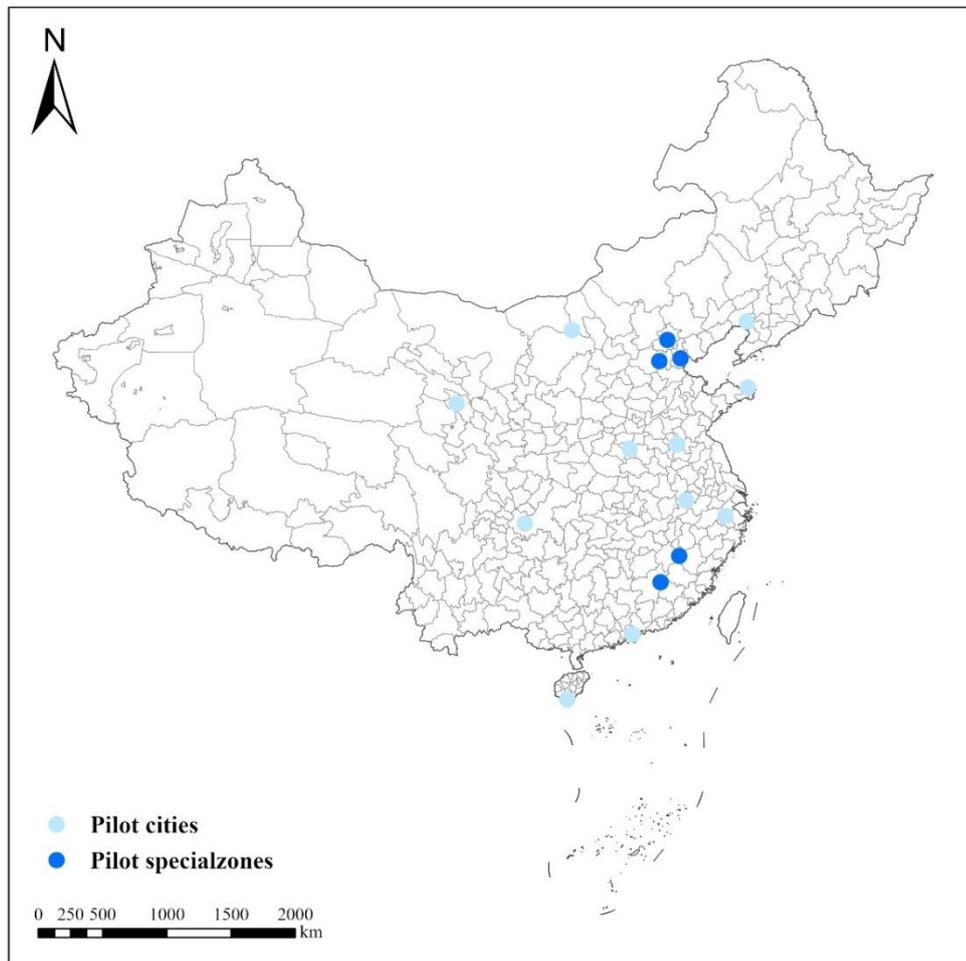
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176 Inspired by prior experience, China has also begun to actively explore a development path for  
 177 zero-waste cities suited to its national conditions. Guided by the new development concept of  
 178 innovation, coordination, green growth, openness, and sharing, the zero-waste city initiative  
 179 represents an urban development model that fosters green growth and sustainable lifestyles (Wang  
 180 & Guo, 2026). It aims to continuously reduce solid waste at the source, maximize resource  
 181 utilization, and minimize landfill volume and the environmental impact of solid waste (Dong et al.,  
 182 2022). The construction of zero-waste cities in China began in early 2018, with the strategic  
 183 objective of minimizing urban solid waste, maximizing resource utilization, and ensuring safe  
 184 disposal. In June of the same year, a central-level document identified zero-waste city development  
 185 as a key task in pollution prevention and control. In December 2018, the General Office of the State  
 186 Council issued a pilot program, planning to select approximately 10 cities to implement  
 187 demonstration projects. In April 2019, the “11+5” pilot reform—featuring cities such as Shenzhen  
 188 and Baotou, as well as related industrial parks and counties—was officially launched. In November  
 189 2021, the Ministry of Ecology and Environment, together with 17 other ministries, jointly issued  
 190 opinions to further promote the classification and resource utilization of household waste. In  
 191 December of the same year, authorities released a comprehensive program for the 14th Five-Year  
 192 Plan period, confirming to the construction of zero-waste cities as an important lever for achieving

193 carbon peaking and carbon neutrality, and building a cross-spatial and temporal indicator system,  
194 providing institutional support for achieving the modernization objective of harmonious coexistence  
195 between humans and nature. At present, the names of the zero-waste pilot areas in China are shown  
196 in Table 1, and the spatial distribution is shown in Figure 3.

197 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



198  
199 Fig. 3. Distribution of ZWCP experimental zones.

### 200 3. Research design

#### 201 3.1 Model setting

202 To systematically evaluate the impact of the ZWCP policy on UCE, the study employs the

203 DoubleML package in a Python 3.12 environment, introducing the DML framework to identify  
 204 causal effects. Compared to traditional methods, DML can effectively mitigate the “curse of  
 205 dimensionality” and reduce model specification errors when dealing with high-dimensional control  
 206 variables. The DML framework primarily incorporates two modes types: Partial Linear Regression  
 207 (PLR) and Interactive Regression Model (IRM) (Bach et al., 2021). The technical roadmap is shown  
 208 in Figure 4.

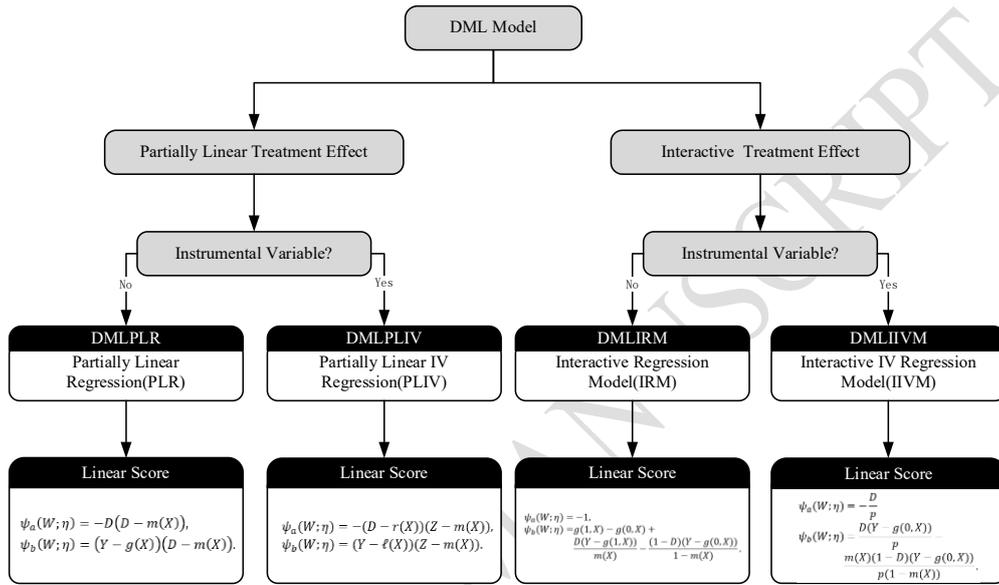


Fig. 4. DML model framework.

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

224 while PLIV and IIVM were used for endogeneity testing. The main regression model was set as  
 225 follows.

$$226 \quad Y_i = \theta_0 D_i + g(X_i) + U_i \quad (1)$$

$$227 \quad D_i = m(X_i) + V_i \quad (2)$$

228 Where,  $Y_i$  is the UCE index, and  $D_i$  is the dummy variable of the ZWCP policy (taking the  
 229 value 1 if the city is included in the pilot program, and 0 otherwise).  $X_i$  is a potential high-  
 230 dimensional control variable set;  $g(X_i)$  and  $m(X_i)$  are unknown functions.  $U_i$  and  $V_i$  are  
 231 random perturbation terms.  $\theta_0$  is the policy effect this paper focuses on (i.e. the causal impact of  
 232 ZWCP on UCE). The PLR model ensures robust estimation of  $\theta_0$  through Neyman  
 233 orthogonalization and cross-fitting. The specific steps are as follows:

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

$$237 \quad \psi_i(\theta, g, m) = (D_i - m(X_i))[(Y_i - g(X_i)) - \theta(D_i - m(X_i))] \quad (3)$$

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

$$239 \quad E[\psi(\theta, g(X_i))] = 0 \quad (4)$$

240 Expanding equation (4), we get:

$$241 \quad E[D_i - m(X_i)](Y_i - g(X_i)) - \theta_0 E[D_i - m(X_i)]^2 = 0 \quad (5)$$

242 Solving for this gives:

$$243 \quad \theta_0 = \frac{E[D_i - m(X_i)][Y_i - g(X_i)]}{E[D_i - m(X_i)]^2} \quad (6)$$

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

$$246 \quad \hat{g}(X_i) \approx g(X_i), \hat{m}(X_i) \approx m(X_i) \quad (7)$$

247 The regularized estimator for  $\theta_0$  is thus:

$$248 \quad \hat{\theta}_0 = \left[ \frac{1}{N} \sum_{i=1}^N (D_i - \hat{m}(X_i))^2 \right]^{-1} \cdot \left[ \frac{1}{N} \sum_{i=1}^N (D_i - \hat{m}(X_i))(Y_i - \hat{g}(X_i)) \right] \quad (8)$$

249 Referencing Chernozhukov's research, it is emphasized that Neyman orthogonalization can  
 250 only ensure that the regularized bias product term converges faster than  $N^{-1/4}$  (a rate typically  
 251 guaranteed by sparsity in regressions like Lasso), thereby avoiding bias from high-order estimation

252 error product terms. However, if machine learning training and residual regression for the target  
 253 parameter residual regression are performed on the same sample batch, a so-called “third term” bias  
 254 (the product of prediction error terms and estimation error terms) will inevitably emerge.

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

$$256 \quad Y_i - \hat{g}(X_i) = \theta_0 D_i + g(X_i) - \hat{g}(X_i) + U_i \quad (9)$$

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

$$258 \quad \frac{1}{\sqrt{N}} \sum_{i=1}^N V_i (Y_i - \hat{g}(X_i)) \quad (10)$$

259 into three parts:

260 a. The product of two error terms, specifically:

$$261 \quad \frac{1}{\sqrt{N}} \sum_{i=1}^N U_i V_i \stackrel{P}{\sim} N(0, \sigma_{UV}^2) \quad (11)$$

262 b. The regularized bias product term, namely:

$$263 \quad \frac{1}{\sqrt{N}} \sum_{i=1}^N (\hat{g}(X_i) - g(X_i)) (\hat{m}(X_i) - m(X_i)) \quad (12)$$

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

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

$$267 \quad \frac{1}{\sqrt{N}} \sum_{i=1}^N V_i (\hat{g}(X_i) - g(X_i)), \frac{1}{\sqrt{N}} \sum_{i=1}^N U_i (\hat{m}(X_i) - m(X_i)) \quad (13)$$

268 Assumption:

$$269 \quad \hat{g}(X_i) = g(X_i) + \frac{U_i}{N^{\frac{1}{2}-\delta}} \quad (14)$$

270 Therefore:

271 
$$\hat{g}(X_i) - g(X_i) = O_p\left(N^{-\frac{1}{2}+\delta}\right) \quad (15)$$

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

274 
$$\frac{1}{\sqrt{N}} \sum_i V_i(\hat{g}(X_i) - g(X_i)) = \sqrt{N}O_p\left(N^{-\frac{1}{2}+\delta}\right) = O_p(N^\delta) \rightarrow \infty \quad (16)$$

275 The final result  $O_p(N^\delta)$  is a quantity that asymptotically diverges as the sample size  $N$   
 276 increases, which means the estimation bias does not disappear but instead continues to increase with  
 277 increasing sample size. This bias primarily stems from the fact that the sample used to estimate  $\hat{m}(\cdot)$   
 278 ) contains information that is potentially correlated with  $V_i$ , making  $V_i$  and  $\hat{g}(X_i) - g(X_i)$   
 279 potentially correlated. In other words, because the same sample is used both to simultaneously  
 280 participate in estimating  $\hat{g}(\cdot)$  and in estimating  $\hat{g}$ 's  $\theta_0$ , this leads to non-negligible estimation bias.

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

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

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

## 291 3.2 Variable definition

### 292 3.2.1 Dependent variable

293 The dependent variable in this paper is estimated urban carbon emissions (UCE). Since the  
 294 scientific validity, robustness, and feasibility of using nighttime light remote sensing data for carbon

295 emission estimation have been confirmed by numerous scholars, this study adopts the approach of  
296 X. Wang et al. (2024) and Wang & Guo (2026). Specifically, the PSO-BP algorithm was used to fit  
297 and train a model linking carbon emissions and nighttime lighting data, ultimately obtaining  
298 spatially consistent and temporally complete UCE data. The specific steps are as follows:

#### 299 I. Data preparation

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

#### 306 II. Data segmentation

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

#### 309 III. Initialize BP neural network and PSO algorithm parameter settings

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

#### 320 IV. Fitness function design

321 The root mean square error (RMSE) was used as the fitness function of the PSO algorithm to  
322 quantitatively evaluate the quality of the network parameter combinations represented by each  
323 particle. RMSE accurately reflects the degree of deviation between the predicted output of the  
324 network and the true target value, with smaller values indicating better network performance. By

325 minimizing RMSE, the PSO algorithm can guide particle swarm to search in the direction of  
326 minimizing the network prediction error, thereby achieving effective optimization of BP neural  
327 network parameters.

#### 328 V. Iterative optimization

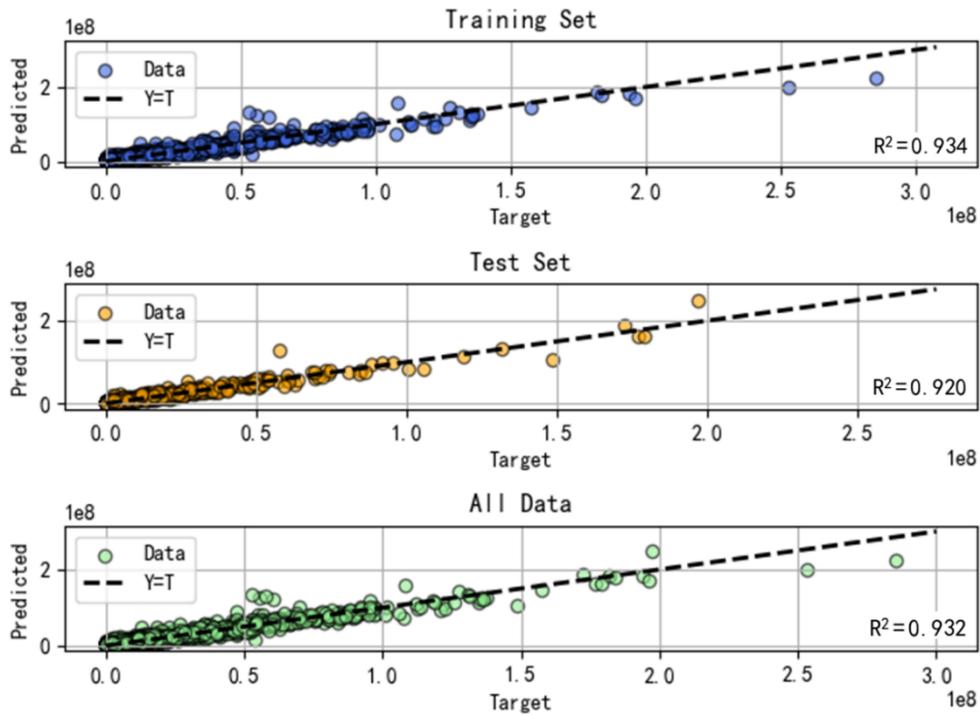
329 In the iterative optimization phase of the PSO algorithm, the velocity and position information  
330 of each particle were dynamically and adaptively updated based on the evaluation results of the  
331 predefined fitness function. The algorithm continuously adjusted the search direction and step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

#### 339 VI. Model training and performance evaluation

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

345 After training, a comprehensive performance evaluation was conducted to assess the model's  
346 effectiveness. The predictive performance and data distribution characteristics were visually  
347 demonstrated by generating a scatter plot analysis between predicted and actual values. The  
348 coefficient of determination ( $R^2$ ) was employed as the core and authoritative evaluation indicator to  
349 quantitatively evaluate the explanatory power of the model for data variability and goodness-of-fit.  
350 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  
351 the  $R^2$  for the entire dataset was 0.932, indicating that the model exhibits excellent fitting ability and  
352 strong generalization ability. The data points in the scatter plot are tightly and consistently  
353 distributed near the ideal prediction line ( $Y=T$ ), which further verifies the high-precision  
354 performance of the PSO-BP hybrid model in predicting UCE. These evaluation results convincingly

355 demonstrate the reliability, applicability and practicality of the model, providing a solid technical  
356 foundation for accurate UCE forecasting and informed policy-making.



357

358

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

359

#### VII. UCE prediction based on urban NTL data

360

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

362

##### 3.2.2 Core explanatory variable

363

364

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  
365 batch of “11+5” ZWCP pilot lists announced by the Chinese State Council in May 2019. The specific  
366 variable assignment method is as follows: for pilot cities, the value of ZWCP from 2019 (inclusive)  
367 onward was set to 1, and the value before 2018 was set to 0. For non-pilot cities, the value was set  
368 to 0 consistently throughout the entire sample period. This coding allows identification of whether  
369 each city was affected by the ZWCP policy and enables evaluation of the carbon reduction effect of  
370 the policy.

371

##### 3.2.3 Control variables

372

The DML model effectively addresses the problem of the curse of dimensionality in controlling

373 variables. Due to the many factors that affect UCE, 12 control variables potentially influencing UCE  
 374 were selected by referring to the research of Byrne et al. (2024) to isolate the pure policy effect.  
 375 These include economic development level, economic development speed, financial development  
 376 level, and degree of government intervention. Following the approach of Ling et al. (2024), the  
 377 quadratic terms of the above variables were added to improve the model fit accuracy and capture  
 378 potential nonlinear relationships. Meanwhile, individual and year dummy variables were introduced  
 379 to control for the fixed effects of cities and time.

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

381 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 ( $gdpg$ )	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 ( $fid$ )	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 ( $lna$ )	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

382

### 383 3.2.4 Data description and descriptive statistics

384 This study employs a panel dataset covering 287 Chinese cities from 2010 to 2022. The control  
 385 variables are compiled primarily from the China City Statistical Yearbook, China Energy Statistical  
 386 Yearbook, China Environmental Statistical Yearbook, China Urban Construction Statistical  
 387 Yearbook, and the annual Statistical Communiqués on National Economic and Social Development.

388 Carbon emission data is sourced from the CEADs database  
 389 (<https://www.ceads.net.cn/data/province/>), while NTL data are obtained from Harvard Dataverse  
 390 (<https://dataverse.harvard.edu/>). Descriptive statistics for the main variables are presented in Table  
 391 3.

392  
 393

Table 3. Descriptive statistic.

Type	Variable	Obs	Mean	SD	Min	Max
Explained variable	<i>lnCO<sub>2</sub></i>	3731	16.918	0.991	13.825	19.552
Core explanatory variable	<i>zwcp</i>	3731	0.107	0.309	0.000	1.000
	<i>gdppc</i>	3731	10.729	0.597	8.576	12.456
	<i>gdpgr</i>	3731	8.162	4.329	-20.630	25.100
	<i>fdl</i>	3731	1.520	0.774	-0.371	20.100
	<i>gi</i>	3731	0.076	0.028	0.023	0.240
	<i>fo</i>	3731	0.200	0.341	0.000	3.659
	<i>lnpd</i>	3731	5.739	0.908	1.792	7.943
Control variables	<i>fidd</i>	3731	0.002	0.003	0.000	0.029
	<i>lnidl</i>	3731	13.411	1.048	9.210	17.762
	<i>lhc</i>	3731	0.018	0.021	0.000	0.129
	<i>lnta</i>	3731	8.009	1.315	1.609	12.184
	<i>ste</i>	3731	0.015	0.030	0.000	0.936
	<i>lntr</i>	3731	8.021	1.846	1.099	12.583

394 4. Empirical analysis

395 4.1 Baseline estimation results

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

407

Table 4. Baseline regression result.

	$\ln CO_2$	$\ln CO_2$	$\ln CO_2$	$\ln CO_2$
	(1)	(2)	(3)	(4)
<i>zwcp</i>	-0.121*** (0.039)	-0.124*** (0.040)	-0.117*** (0.044)	-0.112*** (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

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

## 413 4.2 Robustness checks

### 414 4.2.1 Cluster robust

415 DML achieves the required asymptotic convergence speed by keeping the score function  
 416 approximately independent outside the sample through Neyman orthogonalization and cross-fitting  
 417 procedures. However, if the standard cross-fitting method proposed by Chernozhukov et al. is used,  
 418 clustering can cause correlation between the errors of training and testing samples, which  
 419 undermines the premise of “independent and identically distributed” errors. In addition, traditional  
 420 variance estimation must be replaced with a cluster-robust form; otherwise, the statistical  
 421 significance will be systematically exaggerated. To effectively solve this problem, all cities and  
 422 years were randomly grouped in two-dimensional structure following the approach of Chiang et al.  
 423 (2021). In the subsequent iterations, only one “city group x year group” grid was designated as S in  
 424 each iteration, and the remaining grids were designated as N, ensuring that S and N were completely  
 425 separated in both city and year dimensions. This approach overcomes the sample correlation  
 426 problem caused by standard cross-fitting procedures and ultimately obtains the robust, clustered-  
 427 adjusted standard error  $\hat{\sigma}$  ultimately.

$$428 \quad \hat{\sigma} = \sqrt{\hat{f}^{-1} \hat{\Gamma} \hat{f}^{-1}} \quad (17)$$

429 Where,

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

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

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

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

#### 444 4.2.2 Add new fixed effects

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

454 4.2.3 Adjust the research sample

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

468 4.2.4 Elimination of outliers

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

479

Table 5. Robustness check I.

	Cluster robust	Province - time trends	Delete center city	1%	5%
	(1)	(2)	(3)	(4)	(4)
<i>zwcpc</i>	-0.220* (0.053)	-0.108*** (0.042)	-0.112*** (0.043)	-0.122*** (0.043)	-0.103** (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

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

#### 484 4.2.5 Reset the DML model

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

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

502

Table 6. Robustness check II.

	IRM	Kfolds=3	Kfolds=8	Lasso cv	XGBoost
	(1)	(2)	(3)	(4)	(5)
<i>zwcp</i>	-0.117*** (0.025)	-0.123*** (0.044)	-0.110** (0.043)	--0.168*** (0.050)	-0.136*** (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

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

#### 506 4.2.6 Instrumental variable

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

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

532 verify the robustness of the results. Column 2 of Table 7 indicates that the estimated coefficients of  
 533 policy variables remain strongly significantly negative, confirming that the model has successfully  
 534 passed the rigorous endogeneity test.

535 Table 7. Robustness check III.

	PLIV	IIVM
	(1)	(2)
<i>zwcp</i>	-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

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

#### 539 4.2.7 Sensitivity analysis

540 A sensitivity analysis method was carefully employed in this paper to test the potential impact  
 541 of hidden unobserved confounding factors on the research conclusions, aiming to further verify the  
 542 reliability of the estimated carbon reduction effect estimation of the ZWCP policy. Although DML  
 543 can alleviate the problem of omitted variable bias to some extent, there may still be complex  
 544 confounding factors that are difficult to observe or quantify in the policy evaluation process, such  
 545 as the environmental awareness of company decision-makers, implicit policy implementation  
 546 differences among local governments, and informal cooperation networks between regions. These  
 547 unobserved factors may simultaneously affect the intensity of policy implementation and the effect  
 548 of the carbon reduction effect, leading to systematic bias in the estimation of causal effects. In this  
 549 paper, based on the latest research by Chernozhukov et al. (2022), the sensitivity analysis method  
 550 for DML was used to evaluate whether the findings are influenced by unobserved confounding  
 551 factors. Based on the research of Facure & Germano (2021), the sensitivity analysis function from  
 552 the DoubleML package was applied to ensure the reliability of the results. The sensitivity analysis  
 553 is based on three parameters the strength and correlation of confounding:  $cf_y$  and  $cf_d$  and the  
 554 parameter  $\rho$ .  $cf_y$  measures the proportion of residual variance in the outcome explained by  
 555 unobserved confounders;  $cf_d$  measures the proportion of residual variance in the treatment  
 556 representation explained by unobserved confounders;  $\rho$  measures the correlation between the

557 difference of the long and short forms of the outcome regression and the Riesz representer.  
 558 Regarding parameter settings, Chernozhukov et al. argue that confounding should not account for  
 559 more than 4% of the residual variation of the outcome and 3% of the residual variation of the  
 560 treatment. They also argue that the default value of  $\rho$  being 1.0 is conservative and accounts for  
 561 adversarial confounding. Therefore, in this paper, we set  $cf_y = 0.04$ ,  $cf_d = 0.03$ , and  $\rho = 1.0$ .

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

575 Table 8. Sensitivity analysis.

	CI lower	Theta lower	Theta	Theta upper	CI upper	RV
	(1)	(2)	(3)	(4)	(5)	(6)
<i>zwc</i>	-0.213	-0.202	-0.112	-0.021	-0.011	4.259%

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

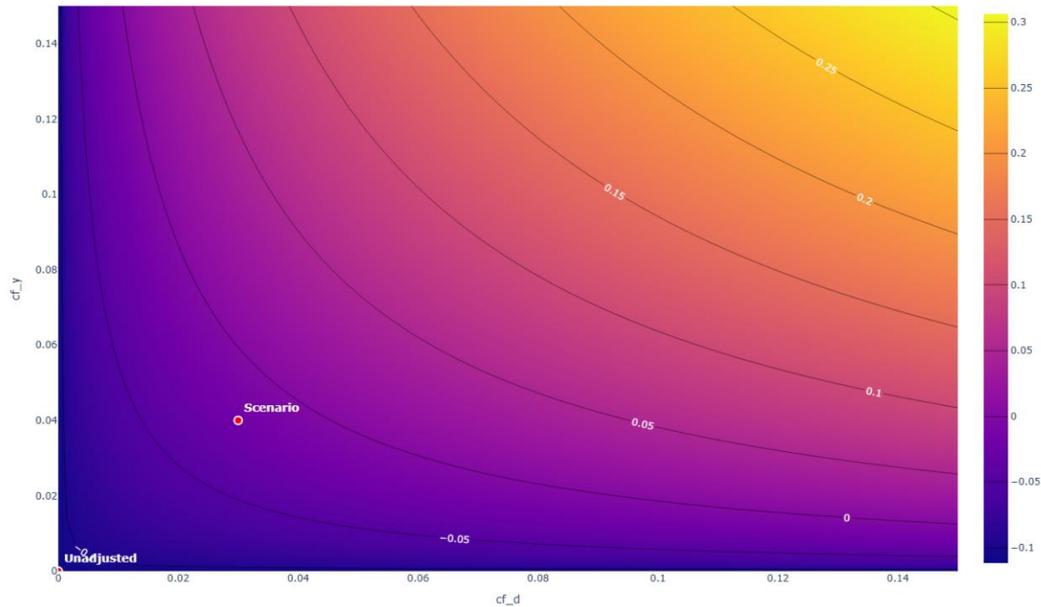


Fig. 6. Contour plot of the sensitivity analysis.

## 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

601 of China on November 12. Thirdly, based on the foundation of industrial development, cities were  
602 categorized as old industrial bases and non-old industrial bases, according to the National Plan for  
603 the Adjustment and Transformation of Old Industrial Bases (2013-2022) approved by the China  
604 Development and Reform Commission in early March 2014.

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

618 The grouped regression results of resource abundance in Table 9 show that the ZWCP policy  
619 has a significant negative effect on carbon emissions in non-resource-based cities, while the effect  
620 is not significant in resource-based cities. Several economic and institutional mechanisms may  
621 underlie the observed differences between these two groups. According to the grouped regression  
622 results of resource abundance shown in Table 9 show that the ZWCP policy has a significant  
623 negative effect on carbon emissions in non-resource-based cities, while the effect is not significant  
624 in resource-based cities. Non-resource-based cities generally rely heavily on service and high-tech  
625 industries, with relatively low energy consumption and carbon emissions, which makes it easier for  
626 these cities to achieve effective reductions in carbon emissions through policy guidance during the  
627 implementation of the ZWCP policy. In addition, they have strong adaptability to adjustments in  
628 industrial structure and the application of green technologies, which enables them to respond  
629 quickly to policy requirements, thereby exerting a stronger policy effect. In contrast, resource-based  
630 cities rely heavily on traditional heavy industry and resource extraction, and their economic models

631 are highly dependent on fossil fuels. These cities face a high baseline of carbon emissions, making  
 632 it difficult to observe immediate policy effects due to the substantial investments required for  
 633 transformation. In addition, resource-based cities tend to respond more slowly to policy incentives,  
 634 hindered by insufficient technological foundations and market mechanisms to effectively support  
 635 policy goals, which hinders the achievement of emission reduction effects.

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

653 Table 9. Group Average Treatment Effect.

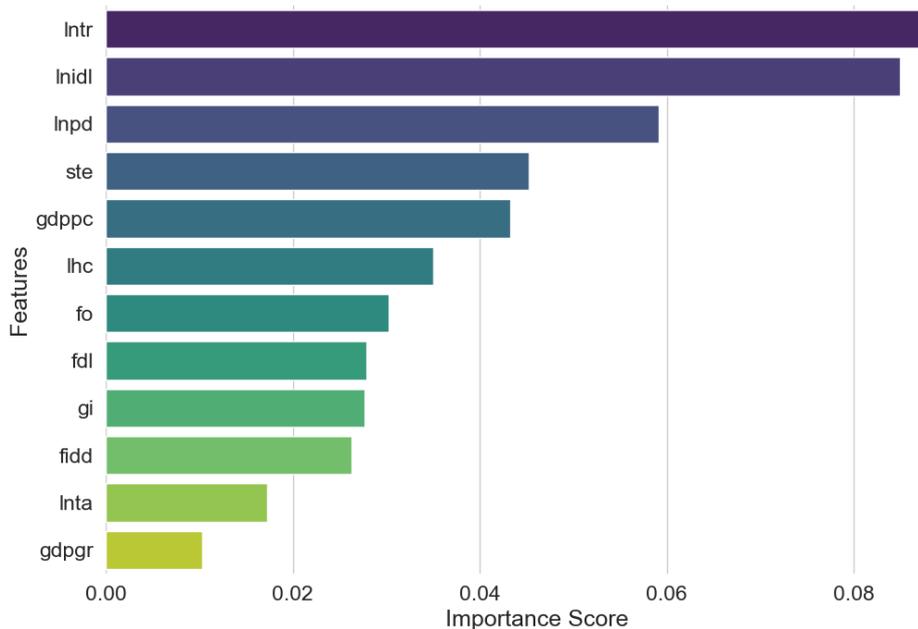
	Geographical location		Resource endowment		Industrial Development	
	Key	Non-Key	Affluence	Lack	Old	Non-Old
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Policy</i>	-0.150** (0.061)	-0.093 (0.064)	-0.083 (0.074)	-0.145*** (0.054)	-0.152** (0.076)	-0.104* (0.053)
Control (single term)	Y	Y	Y	Y	Y	Y
Control (quadratic term)	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
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654 Note: The dependent variable is urban carbon emissions. Robust standard errors are reported in parentheses.  
655 \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

656 5.2 Heterogeneity of city characteristics

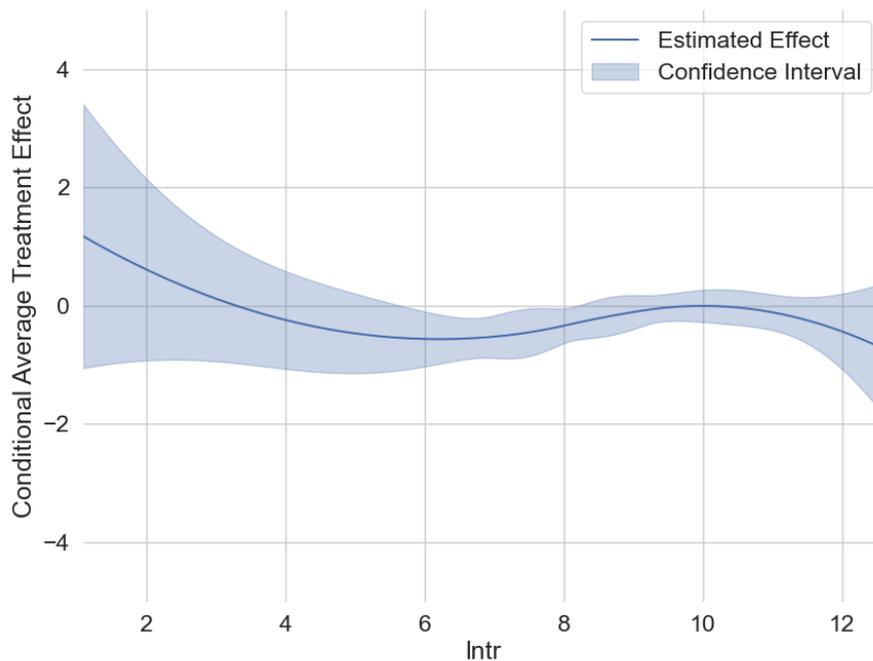
657 Figure 7 shows the ranking results of the importance of control variables obtained using the  
658 random forest model. The two variables that contributed most significantly to the carbon reduction  
659 effect in the construction of zero-waste cities were Science and Technology Research and Internet  
660 Development Level, with importance values exceeding 5%. Therefore, it is necessary to explore  
661 how these two urban characteristics influence the carbon reduction effect of zero-waste city  
662 construction. Accordingly, this paper conducts a heterogeneity analysis based on science and  
663 technology research and internet development level.



664  
665 Fig. 7. Feature importance ranking plot based on random forest.

666 The heterogeneous treatment effect of science and technology research in different areas is  
667 shown in Figure 8. In areas with relatively lower levels of science and technology research, the  
668 regression results of the ZWCP policy were positive, and the carbon emission reduction effect was  
669 relatively weak. This indicates that the policy has some emission reduction effect under certain basic  
670 and limited conditions, but this effect may not be further enhanced due to the lack of efficient  
671 technological support and innovative capabilities. However, the carbon reduction effect of this

672 policy begins to show a markedly significant impact once the level of science and technology  
673 research reaches a certain threshold. This change may be closely related to the substantial  
674 improvement of technological applications and the optimization of resource management efficiency.  
675 With technological advancement, the extensive application of green technology can more  
676 effectively enable waste recycling and reduce greenhouse gas emissions, thus making the zero-waste  
677 city strategy yield more significant emission reductions. Hence, the improvement of science and  
678 technology research is crucial for achieving the expected emission reduction effect of the ZWCP  
679 policy. Policymakers should pay attention to increased investment in science and technology  
680 research, promote technological innovation, and maximize the potential of ZWCP policies, thereby  
681 promoting the achievement of broader and long term carbon reduction objectives.



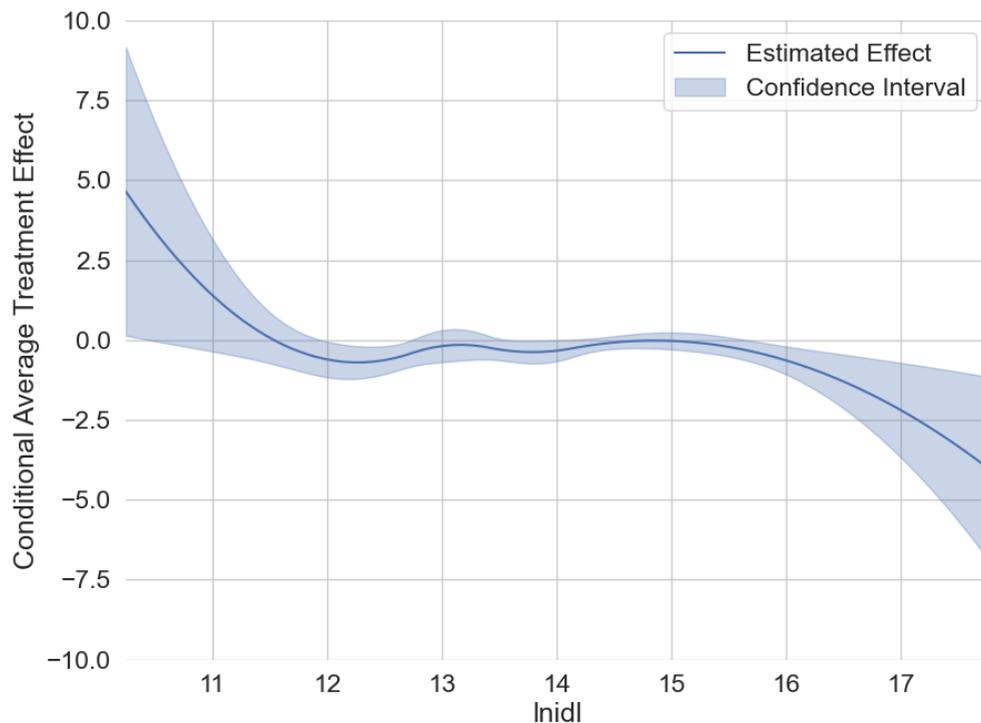
682

683

Fig. 8. CATE of Science and technology research.

684 The heterogeneous treatment effect of Internet development levels in different areas is shown  
685 in Figure 9. The carbon emission reduction effect of the pilot policy for zero-waste cities is positive  
686 in areas with low Internet development, but still relatively limited. This is because, in these areas,  
687 the lower public environmental awareness and participation in environmental protection, along with  
688 insufficient promotion and implementation of environmental measures, result in the inability to fully  
689 demonstrate the effectiveness of the overall policy. However, the situation changes significantly

690 with the improvement of Internet development. The carbon emission reduction effect of zero-waste  
691 cities begins to take a significant effect immediately once the level of Internet development reaches  
692 a certain threshold. This is mainly because Internet development has improved the public awareness  
693 of environmental protection and broadened their understanding of the importance of sustainable  
694 development and waste management. The convenience of information dissemination has  
695 significantly raised society's attention to environmental policies and encouraged more residents to  
696 actively participate in the construction of zero-waste cities. Furthermore, the rapid advancement of  
697 Internet technology greatly facilitates information sharing and the development of green business  
698 models. For example, activities such as waste recycling and reuse through online platforms help  
699 improve the efficiency of resource utilization. These factors work together to dramatically  
700 strengthen carbon emission reduction in areas with developed Internet. Therefore, when  
701 implementing the zero-waste city strategy, policymakers should attach importance to the  
702 development and application of the Internet, with a view to further enhancing the public's  
703 environmental awareness and maximizing the policy's potential for emission reduction with the help  
704 of digital tools and information-sharing mechanisms.



705

706

Fig. 9. CATE of internet development level.

## 707 **6. Conclusions, policy recommendations and limitations**

### 708 6.1 Conclusions

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

### 722 6.2 Policy recommendations

723 Firstly, deepen the connotation of constructing zero-waste cities and scientifically and orderly  
724 expand the scope of pilot projects. The pilot city government should adhere to the concept of “solid  
725 waste industry collaboration,” strengthen the monitoring and evaluation of solid waste’s entire life-  
726 cycle carbon emissions in the pilot areas of zero-waste cities, incorporate carbon reduction targets  
727 into the indicator framework of zero-waste city construction, and guide companies and residents to  
728 practice a “simple, moderate, green, low-carbon, and healthy” lifestyle and consumption pattern.”  
729 On the basis of meeting the current requirements for being declared to be a zero-waste city, the  
730 government should strengthen the assessment standards for “source reduction, comprehensive  
731 resource utilization, and safe disposal,” make synergistic carbon reduction and efficiency gains a  
732 core criterion for selecting pilot cities, consider factors such as development levels and industrial  
733 characteristics of different regions, and prioritize the cities with a strong circular economy  
734 foundation and solid waste treatment capabilities. Moreover, the government should follow a phased  
735 development approach, promptly summarize the carbon reduction experiences of pilot cities in  
736 building the four major guarantee systems of “institutional, market, technological, and regulatory,”

737 form a demonstrable and scalable model for zero-waste city construction. This will help gradually  
738 realize the transformation from “perceived zero-waste” to “circular zero-waste,” and support the  
739 building of a circular “zero-waste society” that contributes to achieving the “dual carbon” goals.

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

757 Thirdly, strengthen technological innovation and digital empowerment, and build a smart zero-  
758 waste city development system. In view of the fact that the improvement of science and technology  
759 research and internet development level can enhance the carbon emission reduction effect of zero-  
760 waste cities, the government should further increase investment in research and development of key  
761 technologies and equipment for solid waste recycling, cultivate a number of leading companies for  
762 solid waste recycling, and establish a comprehensive solid waste big-data-driven intelligent  
763 environmental protection monitoring platform to achieve more precise supervision of the entire  
764 chain of urban solid waste generation, collection, transfer, utilization and treatment. Meanwhile, it  
765 should make full use of Internet technologies to promote the “integration of digital and physical  
766 networks,” establish the industrial chain of renewable resources, promote the recycling of renewable

767 resources, and enhance the circular utilization of urban mines and resources. It should also achieve  
768 synergistic carbon reduction and efficiency improvement by deeply integrating digital technologies  
769 with the construction of zero-waste cities and constructing a circular economy industry chain based  
770 on material flow analysis, thus realizing the “dual carbon” goal.

### 771 6.3 Limitations

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

792

793 **Data Availability Statement:** The original contributions presented in the study are included in the  
794 article, further inquiries can be directed to the corresponding author.

795 **Funding :** This work was supported by the Postgraduate Research & Practice Innovation  
796 Program of Jiangsu Province (Grant No. KYCX25\_4300)

797 **Disclosure Statement:** The authors declare that they have no known competing financial interests  
798 or personal relationships that could have influenced the work reported in this paper.

799

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