frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 20 March 2025
DOI 10.3389/fenvs.2025.1564418

OPEN ACCESS

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RECEIVED 21 January 2025
ACCEPTED 05 March 2025
PUBLISHED 20 March 2025

CITATION
Qian Y, Jiang J, Guo B and Hu F (2025) The impact of "zero-waste city" pilot policy on corporate green transformation: a causal inference based on double machine learning. *Front. Environ. Sci.* 13:1564418.
doi: 10.3389/fenvs.2025.1564418

The impact of "zero-waste city" pilot policy on corporate green transformation: a causal inference based on double machine learning

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Introduction: Against the backdrop of China's ambitious "dual carbon" objectives and ongoing economic transformation, this study investigates the efficacy of solid waste management reform through the "Zero-Waste City" pilot program.

Methods: Utilizing a comprehensive dataset of listed companies from pilot regions spanning 2016-2023, we employ sophisticated double machine learning models to empirically evaluate the program's impact on corporate green transformation.

Results: Our findings demonstrate that the pilot policy implementation significantly accelerates the green transformation trajectory of enterprises within designated regions. Through rigorous mechanism analysis, we identify three primary channels through which the policy operates: enhanced green technological innovation, heightened government environmental oversight, and increased investor environmental awareness. Heterogeneity analysis reveals differential policy impacts across ownership structures and industry characteristics, with more pronounced effects observed in non-state-owned enterprises, non-heavily polluting industries, and traditional (non-high-tech) sectors.

Discussion: These nuanced findings provide valuable empirical evidence and policy implications for the strategic expansion of the "Zero-Waste City" initiative during China's 14th Five-Year Plan period, contributing to the broader literature on environmental policy effectiveness and corporate sustainability transitions.

KEYWORDS

"zero-waste city" pilot policy, corporate green transformation, double machine learning, solid waste management, text analysis

1 Introduction

Global climate change has emerged as one of the major challenges facing humanity in the 21st century. To address this challenge, the international community has committed to controlling global greenhouse gas emissions through a series of global climate agreements such as the Paris Agreement (Nordhaus, 2019). As the world's largest carbon emitter, China made a "dual carbon" commitment to the international community in September 2020: to

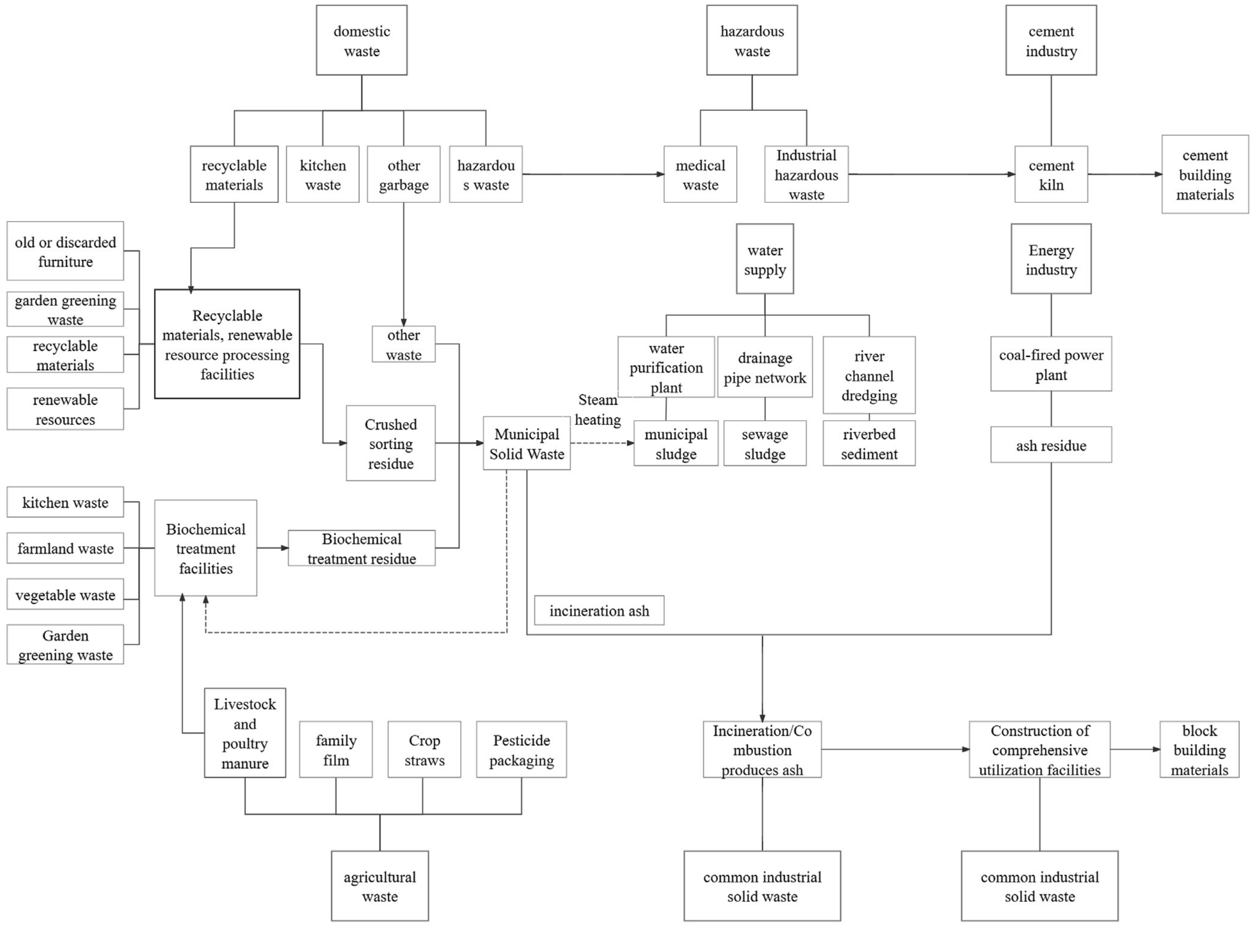

FIGURE 1
Collaborative processing and resource recovery of solid waste.

peak carbon emissions by 2030 and achieve carbon neutrality by 2060. This commitment not only demonstrates China's responsibility as a major global power but also injects new momentum into global climate governance (Zhang et al., 2022). The "2023 State Council Government Work Report" further emphasizes the need to balance energy security and stable supply with green and low-carbon development, advancing carbon peaking and carbon neutrality in a scientific and orderly manner (Wang et al., 2022).

However, during the rapid advancement of industrialization, the extensive resource development and utilization model has led to a continuous increase in solid waste generation, becoming a major constraint in China's pursuit of its "dual carbon" goals (Yu et al., 2022). Data shows that China's annual industrial solid waste generation has exceeded 3 billion tons, with cumulative stockpiles exceeding 60 billion tons, presenting substantial disposal facility deficits. Solid waste not only occupies vast land resources but also causes environmental pollution, affecting ecological system balance (Padilla-Rivera et al., 2020).

To address solid waste management challenges and promote ecological civilization construction, in December 2018, the General Office of the State Council issued the "Pilot Program for Zero-Waste City Construction," proposing an urban development model that continuously advances solid waste source reduction and resource utilization, minimizes landfill volumes, and reduces the environmental impact of solid waste to the lowest level through promoting green development methods and lifestyles. In April 2019, the Ministry of Ecology and Environment announced "11 + 5" Zero-Waste City construction pilots, officially launching China's zero-waste city initiative. In December 2021, the Ministry of Ecology and Environment and other departments issued the "14th Five-Year Plan for Zero-Waste City Construction," clearly proposing that by 2025, the intensity of solid waste generation should decline rapidly and comprehensive utilization levels should improve significantly.

Zero-waste city construction serves as a powerful tool for deepening comprehensive solid waste management reform and promoting the development of a waste-free society at the urban level (Bi et al., 2024a). As the backbone of social modernization, enterprises can play a crucial role in building zero-waste cities under government guidance. Through incentive policies and tax relief measures, enterprises are encouraged to participate in waste sorting and treatment technology development, forming a complete industrial chain and transforming waste treatment into a quality industry. Taking the collaborative and resourceful treatment process of solid waste as an example, through horizontal integration of various solid waste treatments, we achieve coordinated governance of solid waste management. This approach can significantly enhance the utilization efficiency of various environmental sanitation facilities, while reducing overall transportation costs and lowering total carbon emissions, as shown in Figure 1.

The "Zero-Waste City" pilot policy has profoundly impacted corporate green transformation in several ways: First, it requires enterprises to transform their role from passive participants to active bearers of social responsibility, taking responsibility for the entire product lifecycle and constructing a complete system from source innovation to product recycling. Second, through reward policies and tax incentives, the government encourages enterprises to participate in waste sorting and treatment technology development, guiding them to build a complete waste treatment industrial chain. Third, the policy promotes enterprise green production transformation, implementing cleaner production and green design, constructing resource and energy recycling systems across industrial, agricultural, and domestic sectors. Fourth, by participating in zero-waste city construction, enterprises can transform waste treatment into a quality industry, creating new economic growth points. Fifth, enterprises need to cooperate in building intelligent solid waste monitoring systems to achieve whole-process smart closed-loop supervision (Bi et al., 2024b).

Existing literature has extensively discussed the relationship between environmental regulation and corporate green transformation, forming several research streams: First, research on how environmental regulation affects corporate green transformation. Porter and Linde (1995) first proposed that appropriate environmental regulation could incentivize corporate technological innovation, achieving an "innovation compensation" effect. Subsequently, scholars have verified and extended this theory from different perspectives. Chang et al. (2021) found that policy continuity and stability are key factors in promoting enterprise environmental protection technology investment. Zhai and An (2020) pointed out that environmental technology standards promote manufacturing green transformation through technological reformation pathways (Niazi et al., 2023). proposed that corporate green transformation requires managing relationships between enterprises and nature, society, and internal corporate systems to achieve "dual health" of the planet and humans. Ali et al. (2017), examining the impact of mandatory CSR disclosure on corporate green transformation, found that CSR disclosure drives corporate green transformation by strengthening enterprises' regulatory and normative legitimacy. Krass et al. (2013), based on empirical evidence from China's A-share industrial listed companies during 2008–2016, verified that environmental taxes have a significant forcing effect on corporate green transformation. Second, empirical research on pilot policy effects. Existing studies show that environmental policy pilots have played a positive role in promoting regional green development, although policy effects vary significantly across regions (Zhang et al., 2021). El-Kassar and Singh (2019) pointed out that national big data comprehensive pilot zones have played a significant role in promoting data resource concentration, sharing, circulation, and utilization, catalyzing the enabling effect of data elements and thus playing a key role in promoting corporate green transformation and sustainable development. Third, research on how policy design influences implementation effects. Qiu et al. (2021) found that policy goal clarity and implementation tool operability significantly impact policy implementation effects based on low-carbon city pilot policy research. Feroz et al. (2021) further pointed out that digital empowerment can enhance environmental policy implementation efficiency.

However, existing research still has the following limitations: First, although scholars have deeply explored the relationship between environmental regulation and corporate green transformation, research on the "Zero-Waste City" pilot policy as a novel environmental regulation tool is relatively insufficient. In particular, there is a lack of systematic theoretical analysis and empirical testing regarding how the policy influences corporate decision-making (Lu, 2019). Second, existing studies mainly focus on the macro-level effects of the pilot policy, with limited exploration of its mechanisms and transmission paths at the micro-level of enterprises. Gangi et al. (2020) pointed out that understanding corporate-level policy responses is crucial for improving environmental governance. Third, in terms of research methods, traditional econometric methods may suffer from endogeneity and omitted variable issues, affecting the reliability of causal inference (Andrews et al., 2019).

Based on these considerations, this study selects listed companies from China's "Zero-Waste City" pilot areas during 2016–2023 as research samples, employing double machine learning models to systematically examine the impact of the pilot policy on corporate green transformation. Compared to existing research, this paper's marginal contributions are reflected in three aspects: First, it systematically explores the effects, mechanisms, and heterogeneity characteristics of the "Zero-Waste City" pilot policy on corporate green transformation, enriching theories related to environmental policy and corporate behavior. By constructing a theoretical analysis framework, it reveals multiple pathways through which policy influences corporate green transformation, providing new perspectives for understanding the micro-level mechanisms of environmental regulation. Second, methodologically, this paper introduces double machine learning models for empirical analysis, effectively controlling for covariate effects and significantly improving the accuracy and reliability of causal inference. Third, regarding research data, this paper constructs a corporate green transformation evaluation system based on multi-source textual data using machine learning techniques. Through keyword extraction and analysis, it provides new analytical frameworks and empirical tools for quantitative assessment of corporate green transformation, expanding existing measurement methods in corporate green transformation research.

2 Institutional background and theoretical hypotheses

2.1 Background of ZWCP (zero-waste city pilot policy)

The concept of a "zero waste" society emerged as a global environmental paradigm in the early 21st century, aligned with broader sustainable development objectives (Assi et al., 2020). Nations worldwide have institutionalized this vision through comprehensive legislative and policy frameworks. Japan pioneered this movement by enacting the "Basic Law for Establishing a Sound Material-Cycle Society" in 2000, subsequently reinforcing its commitment through the "Fourth Basic Plan" in 2019, which delineated seven national initiatives with quantifiable targets for 2025. The European Union demonstrated its dedication to this cause by introducing two landmark policies in 2014: "Towards a Circular Economy: A Zero Waste Programme for Europe" and the "Circular Economy Package," establishing a comprehensive framework for waste reduction and resource efficiency. Similarly, Singapore articulated its ambitious vision of becoming a "zero-waste" nation in the "Sustainable Singapore Blueprint 2015," integrating waste minimization into its national development strategy. This environmental paradigm shift has gained particular traction at the municipal level, where cities serve as laboratories for innovative waste management approaches (Kurniawan et al., 2020). Metropolitan centers such as San Francisco, Vancouver, and Stockholm have emerged as pioneers, developing sophisticated zero-waste urban planning frameworks (Zaman and Lehmann, 2013). The C40 Cities Climate Leadership Group, a network of the world's megacities committed to addressing climate change, has achieved remarkable progress in advancing zero-waste initiatives, demonstrating the effectiveness of city-level action in driving environmental transformation (Sancino et al., 2021). Against this backdrop of global zero-waste initiatives and municipal innovations, China has emerged as a significant player in advancing environmental governance concepts. Prior to the zero-waste city initiative, China had already accumulated valuable experience in environmental policy pilots, having successively designated three batches of low-carbon pilot cities in 2010, 2012, and 2017. Existing research on these "dual carbon" policy pilots has demonstrated their effectiveness in driving green innovation among listed companies in pilot regions, partially supporting the "Porter Hypothesis" that appropriate environmental regulations can stimulate corporate technological innovation (Guo et al., 2025). Building upon this successful experience with low-carbon pilots, China has developed its own comprehensive zero-waste city framework, tailored to its unique urban challenges and developmental context.

China's zero-waste city initiative was inaugurated in early 2018, embodying a comprehensive approach to urban solid waste management that emphasizes minimization of waste generation, maximization of resource utilization, and optimization of disposal safety (Li et al., 2022). This initiative gained significant political momentum when the CPC Central Committee and State Council explicitly incorporated zero-waste city pilots into their broader environmental governance framework through the "Opinions on Comprehensively Strengthening Ecological Environmental Protection and Resolutely Fighting the Battle Against Pollution" (Zhang and Teng, 2023). The policy framework was further solidified in December 2018 when the General Office of the State Council issued the "Zero-Waste City Construction Pilot Work Plan," establishing guidelines for selecting approximately ten pilot cities. The program's implementation phase commenced in April 2019 with the designation of "11 + 5" pilot cities and regions, with Shenzhen and Baotou serving as flagship municipalities in this transformative initiative (Lv and Guo, 2025). The regulatory framework was subsequently enhanced in November 2021 through the collaborative effort of the Ministry of Ecology and Environment and seventeen other governmental departments, resulting in the "Several Opinions on Further Promoting Waste Sorting Work." This was followed by a crucial policy development in December 2021: the release of the "14th Five-Year Plan for Promoting Zero-Waste City Construction Work." This comprehensive plan strategically positions zero-waste city development as a fundamental component of China's carbon peaking and neutrality objectives, introducing sophisticated indicator systems that operate across urban spatial and temporal dimensions (Meng et al., 2021).

2.2 Theoretical analysis and research hypotheses

Guided by the new development concept, zero-waste city construction aims to organically combine solid waste management with economic and social development. Through optimizing urban spatial layout, adjusting industrial structure, innovating production methods, and transforming lifestyles, it achieves resource conservation and environmental protection objectives. From the characteristics and core concepts of zero-waste city construction and green transformation, this policy is expected to promote corporate green transformation. Although initially, zero-waste city construction may increase corporate burdens through mandatory standards and tasks, as the policy progresses, it will gradually demonstrate "compensation effects" and "growth effects" (Qin et al., 2022). The policy's continuity and stability will incentivize enterprises to invest in solid waste recycling and utilization technologies and adjust production modes, thereby offsetting environmental protection costs (Su, 2020). Based on this, this paper proposes Hypothesis 1.

Hypothesis 1: ZWCP accelerates green and low-carbon transformation in pilot areas.

The Zero-Waste City Pilot Policy (ZWCP), as a new exogenous mandatory environmental regulation measure, ultimately aims to foster waste-free enterprises and industries, thereby achieving a green and low-carbon urban development model. This policy influences corporate green transformation through multiple mechanisms. From the perspective of green technological innovation, policy continuity and stability will drive enterprises to invest in various solid waste recycling and utilization technologies and transform their production methods (Peng et al., 2022). The policy increases innovation pressure on enterprises, reducing innovation uncertainty through increased research investment and financial support, ensuring enhanced enterprise innovation capabilities. Through technological innovation, enterprises are promoted to transition from traditional production modes characterized by high input, high output, high energy consumption, and high pollution to material-saving, energy-saving, and low-carbon production modes, thus achieving green transformation and upgrading (Tang et al., 2023). From the perspective of government environmental attention, various levels of government departments have significantly enhanced their environmental focus on ZWCP pilot areas and implemented green manufacturing system construction. Almost all pilot cities have established ZWCP construction working groups led by municipal party secretaries and mayors as dual group leaders, incorporating ZWCP construction effectiveness into the

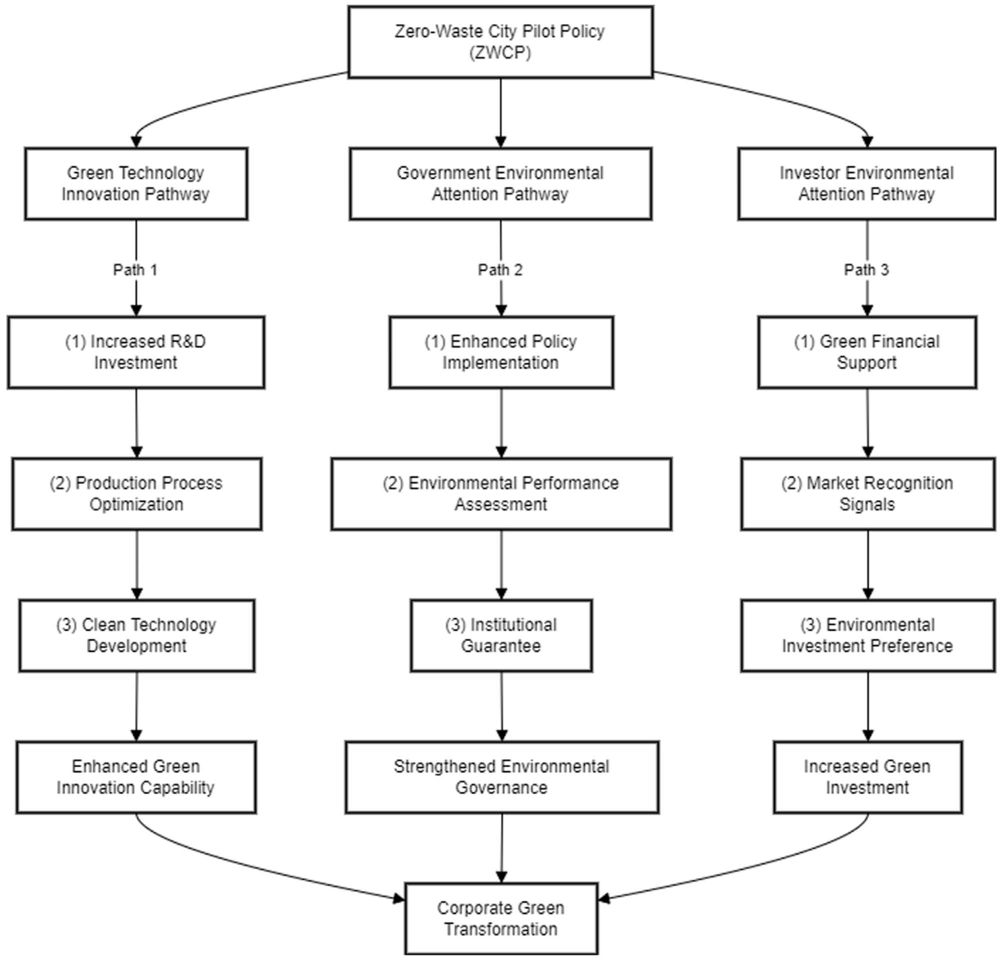

FIGURE 2
Transmission mechanism.

performance evaluation criteria of pilot regions. This top-down environmental attention mechanism provides strong institutional guarantees and policy support for corporate green transformation. From the perspective of investor environmental attention, the policy emphasizes increasing financial support for pilot areas, providing enterprises with greater profit potential. Through green finance and other means, it provides financing support for energy-saving and environmental protection industries, encouraging innovation in financial instruments such as green credit and green bonds, which can induce corporate green innovation (Xie et al., 2024). Investors' environmental attention not only provides financial support for corporate green transformation but also conveys market recognition signals for environmentally friendly enterprises, further promoting corporate development toward green and low-carbon directions. The transmission mechanism of this paper is shown in Figure 2. Based on these considerations, this paper proposes Hypothesis 2.

Hypothesis 2: ZWCP promotes corporate green transformation by enhancing green technological innovation levels, government environmental attention, and investor environmental attention. Specifically:

(a) Green technological innovation serves as a mediating factor between the pilot policy and corporate green transformation;
(b) Government environmental attention serves as a mediating factor between the pilot policy and corporate green transformation;
(c) Investor environmental attention serves as a mediating factor between the pilot policy and corporate green transformation.

3 Research design

3.1 Model specification

This study employs the Double Machine Learning (DML) framework to investigate the causal effect of zero-waste city pilot policy on corporate green transformation. This methodological choice is particularly motivated by the need to address the "curse of dimensionality" and potential functional form misspecification risks in the presence of high-dimensional control variables.

The theoretical framework begins with a partially linear model specification (Chernozhukov et al., 2018). We express the relationship between corporate green transformation ($Green_i$)

and the zero-waste city pilot policy ($Event_i$) through the following equations:

$$Green_i = \alpha_0 Event_i + g(X_i) + U_i \tag{1}$$

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

where α_0 represents our parameter of interest - the policy effect, X_i denotes the high-dimensional control variables, and $g(\cdot)$ and $m(\cdot)$ are unknown nuisance functions.

To ensure robust inference of the main parameter α_0,we implement Neyman orthogonalization. This approach constructs moment conditions that are robust to estimation errors in the nuisance components:

$$\psi(\alpha, g, m) = (Event_i - m(X_i))[Green_i - g(X_i) - \alpha(Event_i - m(X_i))] \tag{3}$$

The estimation procedure incorporates cross-fitting to mitigate potential overfitting concerns and ensure valid inference. This involves randomly partitioning the sample into S folds, training machine learning models on complement sets, computing residuals on each fold, and averaging estimates across folds. This approach effectively separates the sample used for nuisance function estimation from that used for parameter estimation.

The DML framework offers several advantageous properties for our analysis. First, it accommodates non-linear relationships in high-dimensional settings. Second, it allows for the integration of various machine learning algorithms in the estimation of nuisance functions. Third, the resulting estimator exhibits asymptotic normality and achieves √N-convergence rates under suitable regularity conditions. Finally, it enables valid statistical inference and the construction of confidence intervals for the treatment effect.

This methodological approach provides a robust foundation for examining the causal relationship between zero-waste city pilot policy and corporate green transformation, while addressing the complexities inherent in high-dimensional economic data analysis.

3.2 Variable definitions and data sources

3.2.1 Dependent variable

Corporate Green Transformation (*Green*)[(1)]: Following existing literature (Wu and Li, 2022), we employ text analysis methods to construct a corporate green transformation indicator. Specifically, we systematically collected multi-source textual data from A-share listed companies between 2016-2023, including annual reports, corporate social responsibility reports, sustainability reports, environmental reports, and ESG reports. Natural Language Processing (NLP) techniques were applied to quantify information related to corporate green transformation. The indicator construction process involves the following steps:

In the text preprocessing stage, we utilized Python's jieba word segmentation tool to process 36,705 text samples. Given the technical nature of corporate reports, we supplemented the standard dictionary with specialized green transformation vocabulary and implemented stop-word filtering for text cleaning to improve segmentation accuracy. To ensure quality, we employed stratified sampling for manual verification and correction of the word segmentation results, guaranteeing accuracy and reliability.

For text vectorization, we adopted a combined approach using the Bag of Words model and TF-IDF (Term Frequency-Inverse Document Frequency) weighting method. Specifically, we first converted the text into word frequency matrices using the Bag of Words model, then applied TF-IDF weighting to the frequencies. The TF-IDF method considers both the frequency of terms within individual documents (TF) and introduces inverse document frequency (IDF) to reduce the weight of common words, thereby highlighting distinctive keywords. This approach enables more precise capture of key information reflecting corporate green transformation. To eliminate the impact of varying report lengths, we applied logarithmic transformation to the final word frequencies.

The green transformation indicator developed in this study offers three significant advantages over traditional environmental disclosure indices: 1) Information Completeness: Integration of multi-source textual data provides more comprehensive information coverage. 2) Objectivity: Machine learning-based text analysis effectively reduces subjective scoring bias. 3) Accuracy: The incorporation of TF-IDF weighting enhances the precision of key information identification. These advantages enable our constructed indicator to more accurately reflect the level of corporate green transformation.

3.2.2 Explanatory variable

Zero-Waste City Pilot Program (*Event*): A significant environmental governance initiative was launched in January 2019 when the General Office of the State Council promulgated the "Zero-Waste City Construction Pilot Work Plan (Liu et al., 2024)." This comprehensive policy framework was collaboratively implemented by 18 central government departments, with the Ministry of Ecology and Environment assuming a leading role. We leverage this policy intervention as a quasi-natural experiment, employing the Double Machine Learning (DML) methodology to rigorously evaluate its causal effects. Drawing upon the official "Zero-Waste City Construction Pilot List" issued by the Ministry of Ecology and Environment in 2019, we construct a binary treatment indicator that assigns a value of 1 to cities designated as pilot zones following the policy's implementation, while maintaining a value of 0 for non-pilot cities and pre-implementation periods. This identification strategy enables us to isolate the policy's impact through a carefully structured difference-in-differences framework within the DML context.

3.2.3 Control variables

The Double Machine Learning methodology employs an automated variable selection process from a comprehensive candidate pool, optimizing predictive accuracy while mitigating concerns of variable redundancy. To ensure robust policy evaluation, following the empirical frameworks established by Wan et al. (2021) and Fang et al. (2024a), we incorporate a carefully curated set of control variables that potentially influence corporate green transformation: Firm Size (*Size*): Operationalized as the natural logarithm of total assets, this metric accounts for heterogeneity in organizational resource endowments. Leverage Ratio (*Lev*): Defined as the ratio of total liabilities to total assets, this indicator captures the firm's financial structure and risk profile. Revenue Growth Rate (*Growth*): Measured through year-over-year changes in operating revenue, this variable reflects the firm's growth trajectory and market expansion capabilities. Cash Flow Ratio (*Cashflow*): Computed as net operating cash flow scaled by total assets, this measure assesses the firm's operational efficiency in generating cash resources. CEO Duality (*Dual*): A binary indicator taking the value of 1 when the positions of chairman and CEO are consolidated under single leadership, and 0 otherwise, controlling for governance structure variations. Herfindahl-Hirschman Index (*HHI*): Incorporated to quantify industry concentration and competitive dynamics, providing insights into market structure characteristics. Firm Age (*Age*): Calculated as the temporal span between firm establishment and the observation year, this variable accounts for organizational maturity and lifecycle effects.

Drawing upon the methodological innovations of Zhang and Li (2023), we enhance our Double Machine Learning framework by incorporating quadratic specifications for all continuous variables to capture potential complex nonlinear relationships within our model. To optimize the high-dimensional covariate selection, we implement a LASSO regularization framework with a three-tier multicollinearity governance mechanism. First, we determine the optimal LASSO penalty coefficient λ through five-fold cross-validation, minimizing prediction mean squared error across validation sets. The optimization process employs a grid search strategy over λ∈[1e-4, 1e4] on a logarithmic scale, accelerated by Bayesian optimization algorithms. Second, we conduct Bootstrap resampling (1,000 iterations) to assess feature selection stability, retaining only covariates with selection probability exceeding 80%. Third, we verify model identifiability by monitoring the condition number κ(X) of the design matrix XˆT X, maintaining κ < 10ˆ3 as the threshold criterion. This sophisticated econometric approach offers dual advantages: it efficiently manages high-dimensional control variables while employing an automated selection mechanism to identify the most pertinent predictors, thereby substantially enhancing the precision of our parameter estimates. Furthermore, to address potential endogeneity concerns arising from unobservable heterogeneity, we augment our specification with a comprehensive set of fixed effects at both the temporal (year) and entity (firm) levels, ensuring robust identification of our key parameters of interest.

3.2.4 Mediating variables

Green Technology Innovation (*GTI*): Building upon the methodological foundations established by Calel and Dechezleprêtre (2016) and Xu et al. (2021), we operationalize green technology innovation through the natural logarithm of green patent applications (lnpatent). Our deliberate selection of patent applications over granted patents is methodologically motivated by the considerable temporal gap inherent in the patent granting process. This time lag could potentially mask the contemporaneous relationship between green innovation initiatives and corporate environmental transformation. Patent application data offers a more contemporaneous indicator of firms' innovative endeavors, thereby enabling us to capture the dynamic evolution of corporate innovation behavior in response to policy interventions with greater precision. This measurement approach provides a more sensitive instrument for detecting the immediate strategic adjustments in firms' innovative activities following environmental policy implementation.

Government Environmental Attention (*GEA*)[(2)]: As a city-level exogenous environmental governance initiative, the Zero-Waste City pilot program affects corporate green transformation primarily through its influence on local governments' environmental management priorities. The program serves as an institutional catalyst that heightens environmental awareness among local authorities, who subsequently drive corporate green transformation through a combination of policy instruments and regulatory oversight. Drawing on the methodological framework developed by Shen et al. (2020), we systematically analyze Government Work Reports collected from prefecture-level city official portals. Through careful content analysis, we identify and track 53 environment-related key terms. To quantify local government environmental attention, we construct a composite indicator by computing the natural logarithm of these keywords' occurrence frequency. This measurement approach yields a continuous scale where higher values correspond to stronger governmental focus on environmental issues, allowing us to capture variations in policy emphasis across different administrative regions.

Investor Environmental Attention (*IEA*)[(3)]: The implementation of the Zero-Waste City Pilot Program may catalyze corporate green transformation through its influence on investor attention to environmental stewardship initiatives. To empirically capture this transmission mechanism, we adopt a sophisticated textual analysis approach developed by Xiong et al. (2023), leveraging comprehensive investor-company interaction transcripts as our primary data source. Our methodological framework involves systematic content analysis of investor inquiries during company interactions. Specifically, we employ a binary classification system: questions containing environmental protection-related terminology are coded as 1, signifying heightened investor awareness and prioritization of corporate environmental initiatives, while other inquiries are coded as 0. To construct our final measure, we aggregate the frequency of environment-focused questions for each listed company on an annual basis and apply logarithmic transformation to address potential scaling issues and enhance distributional properties. This refined indicator provides a quantitative measure of investor environmental attention that captures both the intensity and evolution of market participants' environmental focus.

This investigation utilizes comprehensive economic data from Chinese A-share listed companies over an 8-year period (2016–2023). To ensure data quality and analytical robustness, we implemented a systematic sample selection protocol with the following exclusion criteria: 1) financial sector enterprises, due to their distinct regulatory environment and accounting practices; 2) companies designated as ST, *ST, or those delisted during the study period, to avoid potential distortions from financially distressed firms; and 3) entities exhibiting substantial missing data, to maintain analytical integrity. The resulting dataset encompasses 25,645 firm-year observations, providing a robust foundation for empirical analysis. The study draws from multiple authoritative databases to ensure comprehensive and reliable data coverage. Corporate financial information was extracted from the CSMAR (China Stock Market and Accounting Research) database, while patent-

TABLE 1 Descriptive statistics.

Var	(1)	(2)	(3)	(4)	(5)
	Obs	Mean	SD	Min	Max
Green	25645	3.5625	0.9492	0.0000	7.7832
Event	25645	0.3403	0.4738	0.0000	1.0000
Size	25645	22.3048	1.3011	19.7343	26.4523
Lev	25645	0.4096	0.2036	0.0487	0.9343
Growth	25645	0.3326	0.8392	−0.9258	8.0791
Cashflow	25645	0.0481	0.0676	−0.1948	0.2656
Dual	25645	0.3288	0.4698	0.0000	1.0000
HHI	25645	0.1888	0.1657	0.0412	1.0000
Age	25645	3.0222	0.3063	1.3863	4.2905
GTI	25645	1.0134	1.3086	0.0000	7.4390
GEA	25645	8.7401	0.4482	0.6931	9.6709
IEA	25645	1.3863	1.1308	0.0000	6.8711

related data was obtained from the CNRDS (China Research Data Services) platform. Corporate disclosures and reports were sourced from the Juchao Information Network, China's designated repository for listed company information. Regional macroeconomic indicators were compiled from respective provincial statistical yearbooks to control for geographical economic variations.

Table 1 presents the descriptive statistics for all variables under investigation.

4 Empirical analysis

4.1 Baseline regression

To eliminate the correlation between residual terms and estimation errors (i.e., to avoid endogeneity problems caused by sample overlap), this paper employs the cross-fitting approach proposed by Chernozhukov et al. (2018) for double machine learning empirical analysis. In the experimental design, we adopt a 1:4 sample splitting ratio and use the LASSO regression algorithm for cross-fitting estimation of main and auxiliary regressions, with results shown in Table 2. The empirical analysis consists of three levels: First, in the baseline model controlling only for firm and year fixed effects (Column (1)), the estimated coefficient of the core explanatory variable is 0.1154, significant at the 5% level, preliminarily verifying that the Zero-Waste City Pilot Program (ZWCP) has a significant promoting effect on corporate green transformation. Second, to mitigate potential omitted variable problems, we gradually introduce first-order terms (Column (2)) and second-order terms (Column (3)) of control variables based on the baseline model. The results show that under all model specifications, the estimated coefficients of the core explanatory variable Event maintain robust positive effects at the 5% significance level, strongly confirming that the ZWCP can significantly enhance the level of corporate green transformation in pilot areas, thereby validating Hypothesis 1 of this study.

TABLE 2 Baseline regression.

Var	(1)	(2)	(3)
	Green	*Green*	*Green*
Event	0.114***	0.037***	0.036***
	(0.012)	(0.012)	(0.012)
_cons	−0.000	0.001	0.001
	(0.006)	(0.004)	(0.004)
Control (single term)	YES	YES	YES
Control (quadratic term)	NO	NO	YES
Year FE	NO	YES	YES
Firm FE	NO	YES	YES
Obs	25645	25645	25645

Standard errors in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01.

TABLE 3 Robustness checks I.

Var	(1)	(2)	(3)	(4)
	Green	*Green*	*Green*	*Green*
Event	0.037***	0.041***	0.036***	0.036***
	(0.012)	(0.012)	(0.012)	(0.012)
_cons	0.002	0.002	0.001	0.001
	(0.004)	(0.003)	(0.004)	(0.004)
Control (single term)	YES	YES	YES	YES
Control (quadratic term)	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Obs	25645	25645	25645	25645

Standard errors in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01.

4.2 Robustness checks

To ensure the validity of our findings, we conduct a comprehensive series of robustness tests examining the impact of the Zero-Waste City Pilot Program (ZWCP) on corporate green transformation.

4.2.1 Alternative sample splitting ratios

Building upon the methodology of Zhang and Li (2023), we assess the robustness of our empirical results by implementing alternative sample splitting strategies in our double machine learning framework. We modify the baseline 1:4 sample splitting ratio to 1:3 and 1:5, respectively, and conduct new estimations.

TABLE 4 Robustness checks II.

Var	(1)	(2)	(3)	(4)
	Green	*Green*	*Green*	*Green*
Event	0.072***	0.037***	0.045***	0.047***
	(0.014)	(0.012)	(0.015)	(0.013)
_cons	0.002	0.001	15.296	0.002
	(0.005)	(0.004)	(3.481)	(0.004)
Control (single term)	YES	YES	YES	YES
Control (quadratic term)	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Obs	25645	25645	25645	24999

Standard errors in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01.

Table 3 presents these results. Notably, across different sample splitting specifications (1:3 in Column (1) and 1:5 in Column (2)), the estimated coefficients of our key explanatory variable Event remain not only statistically significant but also consistently positive, with magnitudes closely aligned with our baseline estimates. This consistency across different specifications strongly reinforces the robustness of our baseline findings and lends additional credibility to our empirical results.

4.2.2 Winsorization analysis

To address concerns about the potential influence of outliers on our estimates, we implement a winsorization procedure at both the 1st and 5th percentiles for all control variables. The estimation results under these alternative specifications are reported in Columns (3) and (4) of Table 3, respectively. Our empirical analysis reveals that even after accounting for extreme observations, the estimated coefficients of Event retain their statistical significance and positive direction, with magnitudes remaining remarkably stable relative to our baseline estimates. This consistency demonstrates that our findings are robust to the treatment of outliers, providing compelling evidence that the documented positive effect of the ZWCP on corporate green transformation is not driven by extreme observations.

4.2.3 Alternative machine learning specifications

To further substantiate the robustness of our findings, we extend our analysis by implementing diverse machine learning methodologies. Specifically, we augment our baseline LASSO regression framework by employing two alternative state-of-the-art machine learning algorithms: Elastic Net, which combines L1 and L2 regularization, and Gradient Boosting, an ensemble learning approach. The estimation results from these alternative specifications are reported in Columns (1) and (2) of Table 4, respectively. The empirical investigation reveals that across these different machine learning architectures, the estimated coefficients of our key explanatory variable Event maintain their statistical significance and positive directionality with remarkable consistency. The magnitude and significance of these effects

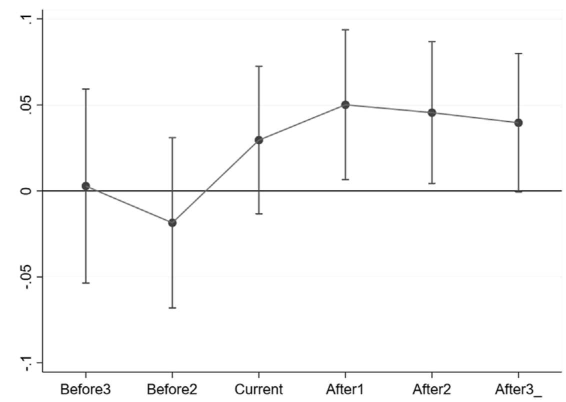

FIGURE 3
Parallel trends test.

remain stable across specifications, lending strong support to our main findings. This methodological consistency across different algorithmic approaches provides compelling evidence that our documented positive relationship between the ZWCP and corporate green transformation is robust to model specification and is not an artifact of any particular machine learning algorithm.

4.2.4 Difference-in-differences analysis

To further address potential concerns regarding omitted variable bias, we employ the traditional difference-in-differences (DID) approach as an additional robustness check. This methodology effectively mitigates endogeneity concerns arising from omitted variables by controlling for time-invariant individual fixed effects and common temporal trends. Column (3) of Table 4 reports the estimation results from the DID model. The coefficient of our key explanatory variable Event remains positive and statistically significant, indicating that our main finding—that the ZWCP promotes corporate green transformation—remains robust under alternative econometric specifications, providing further support for our baseline results. Notably, the validity of the DID approach hinges on the parallel trends assumption. To verify this crucial identifying assumption, we conduct a parallel trends test using 2018 (the year before policy implementation) as the base period. As illustrated in Figure 3, the test results support the presence of similar trends between the treatment and control groups prior to policy implementation, satisfying the key identification assumption of the DID methodology.

4.2.5 Propensity score matching analysis

The inherent design of our key explanatory variable—the Zero-Waste City Pilot Program—exhibits substantial exogeneity in its implementation, providing a strong theoretical foundation to mitigate concerns regarding reverse causality in our regression framework. Nevertheless, we acknowledge that pilot and non-pilot cities may exhibit systematic heterogeneity across multiple dimensions, particularly in terms of economic development trajectories and environmental policy frameworks. Such underlying differences could potentially introduce sample selection bias, necessitating methodological refinements to ensure

TABLE 5 Mechanism analysis.

Var	(1)	(2)	(3)
	Green	*Green*	*Green*
Event	0.027*	0.033***	0.048***
	(0.016)	(0.008)	(0.018)
_cons	0.002	0.001	0.001
	(0.005)	(0.003)	(0.005)
Control (single term)	YES	YES	YES
Control (quadratic term)	YES	YES	YES
Year FE	YES	YES	YES
Firm FE	YES	YES	YES
Obs	25645	25645	25645

Standard errors in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01.

the validity of our policy effect estimates. To rigorously address these identification challenges, we implement a propensity score matching (PSM) methodology to construct a more balanced and comparable analytical sample. Specifically, we employ a one-to-one nearest neighbor matching algorithm with a stringent caliper to optimize the covariate balance between treatment and control observations. Subsequently, we apply our double machine learning framework to this matched sample to re-estimate the treatment effects. The results, presented in Column (4) of Table 4, reveal that the estimated coefficients demonstrate a modest uptick in magnitude while preserving their statistical significance at conventional levels. This consistency in results across different methodological approaches provides compelling evidence for the robustness of our baseline estimates and strengthens the causal interpretation of our findings.

4.3 Mechanism analysis

Given the ongoing academic discourse concerning endogeneity issues in mediation effect models Jiang (2022), we adopt the methodological framework to investigate the transmission mechanisms through which the Zero-Waste City pilot policy affects corporate green transformation. This approach focuses on identifying the causal relationships between core explanatory variables and mechanism variables. The three mechanism variables identified in this study have been confirmed by existing literature to influence green transformation: green technology innovation (Liu et al., 2024), government environmental attention (Chen et al., 2024), and investor environmental attention (Xiong et al., 2023). The corresponding proxy indicators have been presented in the previous sections. The proxy indicators for these variables have been elaborated in previous sections. The empirical results of our mechanism analysis are presented in Table 5. The estimation results in Column (1) reveal that the coefficient of Event is 0.249, which is statistically significant at the 10% level. This finding provides empirical evidence that the Zero-Waste City pilot policy substantially enhances corporate green transformation through the promotion of enterprises' green innovation capabilities. More specifically, enterprises under the policy framework demonstrate increased commitment to green technology research and development initiatives. These innovative practices yield dual benefits: the optimization of production processes and the advancement of cleaner production technologies alongside improved circular resource utilization. Consequently, this facilitates a fundamental transition from conventional production paradigms to environmentally sustainable development models. Columns (2) and (3) report the empirical findings with environmental attention measures as dependent variables. The Event coefficients exhibit statistically significant positive values for both governmental and investor environmental attention metrics. These results strongly suggest that the Zero-Waste City pilot policy generates a dual effect: it enhances policy effectiveness and resource allocation efficiency while simultaneously influencing investors' financing strategies. This dual mechanism strengthens enterprises' commitment to green transformation and catalyzes their progression toward enhanced environmental performance. These empirical findings provide robust support for Hypothesis 2.

4.4 Heterogeneity analysis

4.4.1 Technology level

We investigate the heterogeneous effects of policy interventions across enterprises with varying technological capabilities. Following the methodological framework of (Yao and Wang, 2020), we stratify our sample into high-tech and non-high-tech industries to examine how technological heterogeneity moderates the impact of the Zero-Waste City policy. The empirical results presented in Table 6 reveal an interesting pattern: while the Event coefficient in Column (1) lacks statistical significance, it exhibits strong positive significance in Column (2), suggesting that the policy's efficacy is particularly pronounced in non-high-tech enterprises' innovation activities and green transformation initiatives. This asymmetric effect can be attributed to the inherent characteristics of non-high-tech industries, particularly their substantial resource dependence in manufacturing and traditional service sectors. These industries, characterized by more visible waste generation and pollution intensity in their production processes, demonstrate greater responsiveness to the Zero-Waste City policy's resource management and waste treatment protocols. Furthermore, within non-high-tech industries, green transformation emerges as a strategic differentiator for competitive advantage. The policy framework enables these enterprises to establish environmental leadership positions, consequently enhancing their market positioning and brand equity (Chen et al., 2025). Conversely, high-tech industries, already equipped with advanced innovation capabilities and established environmental protocols, exhibit diminishing marginal returns to additional policy interventions due to their pre-existing technological sophistication in waste management.

4.4.2 Pollution level

To further explore the policy's heterogeneous effects, we examine the moderating role of pollution intensity, categorizing enterprises into heavily polluting and non-heavily polluting entities,

TABLE 6 Heterogeneity analysis.

Var	(1)	(2)	(3)	(4)	(5)	(6)
	Green	*Green*	*Green*	*Green*	*Green*	*Green*
Event	0.001	0.060***	0.006	0.049***	0.062**	0.043***
	(0.023)	(0.014)	(0.044)	(0.013)	(0.026)	(0.014)
_cons	0.006	0.000	−0.002	0.002	0.003	0.001
	(0.006)	(0.004)	(0.012)	(0.004)	(0.007)	(0.004)
Control (single term)	YES	YES	YES	YES	YES	YES
Control (quadratic term)	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Obs	7,057	18588	2,367	23278	7,640	17555

Standard errors in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01.

following Guo et al. (2019). The empirical evidence from Table 6 demonstrates a distinct pattern: while the Event coefficient lacks significance in Column (3), it exhibits robust positive significance in Column (4), indicating enhanced policy responsiveness among non-heavily polluting enterprises. This differential impact can be attributed to several factors. First, the pilot policy's clear regulatory framework and support mechanisms facilitate more efficient adaptation of production processes and management systems among non-heavily polluting enterprises. Second, these enterprises typically possess greater operational flexibility in technological innovation implementation. Conversely, heavily polluting enterprises, subject to long-standing stringent environmental regulations, may exhibit "policy fatigue" toward additional environmental initiatives. The Zero-Waste City framework's specific focus on "industries such as coking, non-ferrous metals, gold, metallurgy, and chemicals" for green mining implementation acknowledges the pre-existing regulatory burden on these heavily polluting sectors.

4.4.3 Ownership structure

Given that the effectiveness of policy interventions may differ across ownership structures, we incorporate state ownership (SOE) as a categorical variable to investigate how ownership heterogeneity moderates the impact of zero-waste city policy implementation. Table 6 presents compelling evidence through event coefficients demonstrating positive significance across both Columns (5) and (6), with notably stronger effects in Column (6), providing robust support for Hypothesis 4c regarding the policy's enhanced impact on non-SOEs. This differential effect can be primarily attributed to the institutional advantages derived from China's mixed-ownership reforms, as recent empirical evidence suggests that private enterprises with state-owned shareholders demonstrate enhanced environmental governance capabilities through dual mechanisms: optimized supervision structures and reduced policy constraints (Guo et al., 2023). Several institutional and organizational factors contribute to this enhanced responsiveness: First, non-SOEs typically demonstrate heightened sensitivity to brand reputation and corporate social responsibility considerations, leveraging policy compliance to enhance stakeholder trust and market positioning. Second, their superior operational agility enables more rapid adaptation of production processes and management systems to meet policy requirements, in contrast to SOEs which often face operational constraints due to multiple policy objectives and rigid budgetary systems (Guo et al., 2025). Third, the streamlined governance structures characteristic of non-SOEs facilitate the swift implementation of circular production models mandated by the Zero-Waste City framework, while their market-oriented positioning provides strong incentives for strategic environmental investments. Moreover, their enhanced responsiveness to market signals and stronger innovation incentives under the policy framework, as emphasized in regulatory documents focusing on "nurturing environmental governance and ecological protection market entities," further enables them to capitalize on environmental cost advantages more effectively.

5 Conclusion and policy recommendations

5.1 Conclusion

China is currently at a crucial stage of economic development. While environmental governance and economic benefits were once viewed as opposing objectives, their synergistic effects actually form the foundation and driving force for sustainable economic development. This study combines the Zero-Waste City pilot policy, implemented in December 2018, with corporate green transformation, employing double machine learning methods to empirically examine their relationship. The findings reveal that the Zero-Waste City pilot policy has significantly promoted green transformation among enterprises in pilot regions. Mechanism tests indicate that this policy encourages corporate green transformation by enhancing enterprises' green innovation levels and increasing environmental attention from both government and investors. Heterogeneity tests further demonstrate that the pilot policy has particularly significant effects on improving green transformation levels in non-high-tech industries, non-heavily polluting enterprises, and non-state-owned enterprises. However, this study has certain limitations. Due to the relatively short implementation period, the 2019–2023 evaluation window primarily captures initial policy responses while potentially missing long-term adaptation dynamics, as observed in Germany's Zero-Waste City transition case. Moreover, the generalizability of our findings may be limited by China's unique institutional context, as international waste management paradigms demonstrate significant variations in policy mechanisms, such as the European Union's Extended Producer Responsibility (EPR) framework emphasizing market-driven approaches and San Francisco's "Pay-As-You-Throw" system achieving 80% waste diversion through economic incentives. This suggests the need for future research to employ extended time series data and cross-national comparative analyses to further validate policy effectiveness.

5.2 Policy recommendations

First, incentivize enterprises to actively participate in Zero-Waste City construction and promote corporate green transformation. Regarding fiscal and tax support policies, environmental protection tax exemptions should be granted to enterprises that legally conduct comprehensive solid waste utilization and meet national and local environmental protection standards. In agricultural support and protection subsidies, increase subsidies for comprehensive utilization of livestock manure and straw for organic fertilizer production while simultaneously reducing chemical fertilizer subsidies and expanding government green procurement of recycled products. In terms of financial support, actively promote green financial instruments such as green credit and green bonds, explore green financial support pilots for livestock waste disposal and harmless treatment, support solid waste utilization and disposal industry development, and establish diversified financing channels. In government-invested public works, prioritize the use of comprehensive utilization products made from bulk industrial solid waste. Meanwhile, accelerate the establishment of incentive and constraint mechanisms promoting solid waste reduction, resource utilization, and harmless treatment, with clear specifications for usage scope and proportion requirements.

Second, green transformation of heavily polluting industries is crucial for future Zero-Waste City achievement, requiring more specific environmental governance plans. The regulatory system for heavily polluting industries should be improved by establishing a city-wide smart supervision information platform for solid waste, achieving comprehensive GPS and video coverage for intelligent monitoring. Empirical evidence from pilot cities has demonstrated the effectiveness of such platforms. For instance, Shenzhen's construction waste smart supervision platform, operated through a "state-owned capital holding + market-oriented operation" mixed-ownership reform model, has achieved remarkable results through three innovative modules: 1) an intelligent sensing layer deploying millimeter-wave radar and weight sensor networks with an error rate below 2.5% for real-time site emission measurement; 2) a blockchain evidence layer based on the Hyperledger Fabric framework, reducing transportation trajectory tampering risks by 92%; and 3) a decision optimization layer using deep Q-learning algorithms for dynamic route planning, reducing average daily mileage by 18.7 km per vehicle (Wang et al., 2024). Another successful case is demonstrated by Hangzhou's "Zero-Waste Cell" IoT system implemented during the Asian Games venue construction, which achieved a 98.4% closed-loop utilization rate for 2,000 tons of event waste through RFID tracking technology. The system's success validates the adaptability of intelligent supervision platforms in time-compressed scenarios through distributed edge computing nodes and digital twin technology for waste diversion path optimization (Fang et al., 2024b). Law enforcement personnel can conduct real-time online inspections of enterprises' solid waste management records and storage standardization through synchronized video, enabling immediate correction of identified issues and forming closed-loop regulatory supervision. Establish a list of key environmental monitoring units for hazardous waste, promote comprehensive intelligent supervision of hazardous waste, and enhance risk prevention capabilities. Improve the environmental credit evaluation system and strengthen joint penalties for dishonest enterprises and practitioners. Fully utilize information technologies such as IoT and GPS to achieve information visualization of solid waste collection, transfer, and disposal, improving supervision efficiency. Establish a multi-level environmental emergency system connecting "enterprise-street-district-city" levels.

Third, solid waste management effectiveness in state-owned enterprises is key to Zero-Waste City construction. Improve assessment mechanisms for state-owned enterprises by incorporating solid waste reduction and resource utilization targets into evaluation systems and establishing comprehensive solid waste management systems. Encourage state-owned capital to increase investment in ecological protection and restoration, supporting technological innovation in solid waste treatment. Actively cultivate third-party markets, encourage specialized third-party institutions to engage in solid waste resource utilization, environmental pollution treatment, and consulting services, fostering leading enterprises in solid waste resource utilization. With government as the responsible entity, promote solid waste collection, utilization, and disposal project implementation and facility operation. While avoiding local government debt increase, legally explore third-party governance or Public-Private Partnership (PPP) models to achieve risk and benefit sharing with social capital.

Fourth, construct a systematic solid waste management innovation system. As the Zero-Waste City policy's effect on high-tech enterprises' green transformation remains unclear, establish a comprehensive technical innovation ecosystem for solid waste management integrating "industry integration, urban-industrial integration, and functional integration" through national and local government funding support. Increase support from green low-carbon development funds and environmental protection special funds, ensuring strong scientific and technological service support. Improve talent recruitment incentive policies in solid waste technical and management fields, promoting high-level scientific and technological innovation talent team building. Develop online trading platforms enabling precise matching between solid waste generators and processors, integrating information about waste generation units, processing units, transportation units, and detailed waste conditions and treatment requirements. High-tech enterprises should establish solid waste research platforms, creating technology demonstration and achievement transformation bases. Through setting up research projects (special programs, funds), identifying industry demands, publicizing project information, promoting achievement transformation, and establishing exchange cooperation, promote effective combination and precise investment of talent, information, capital, and technology, strengthening deep integration of industry-university-research collaboration and collaborative innovation, improving the speed and efficiency of scientific research achievement transformation. Meanwhile, solid waste research platforms can also carry public services, enhancing public participation and achieving collaborative governance.

6 Notes

(1) Keywords for green transformation include: green, low-carbon, green innovation, green transformation, green upgrading, green mountains and clear waters, carbon reduction, carbon verification, ecological restoration, environmental protection management measures, environmental management systems, environmental management procedures, carbon asset management, energy management, three simultaneities, environmental protection investment, refined management, environmental governance, process control, end-of-pipe treatment, carbon management, carbon emission management, lean management, energy efficiency management, accountability system, performance assessment, environmental impact assessment, environmental responsibility, environmental protection officials, environmental supervision, land reclamation, soil and water conservation, efficiency, energy saving, environmental protection, electricity saving, water conservation, sustainable development, development trends, market prospects, environmental optimization, resource regeneration, new energy development, recycling, circular regeneration, green finance, climate change, alternative technologies, carbon footprint, carbon trading, etc.

(2) Keywords for government environmental protection attention mainly include: haze, environmental protection, resources, recycling, global warming, acid rain, greenhouse effect, water conservation, afforestation, greening, dust, smoke, exhaust, atmosphere, clear waters, blue sky, sewage, treatment rate, river chief, green space, beautiful, water source, water consumption, particles, joint prevention, joint control, air quality, environmental protection, pollution, energy consumption, emission reduction, sewage discharge, ecology, green, low-carbon, air, sulfur dioxide, carbon dioxide, sustainable, clean energy, fossil fuels, coal, petroleum, natural gas, solar energy, nuclear energy, recycling, etc.

(3) Keywords for investor environmental protection attention mainly include: environmental protection, pollution, energy conservation and emission reduction, wastewater treatment, etc.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

YQ: Data curation, Methodology, Writing–original draft. JJ: Supervision, Validation, Writing–review and editing. BG: Investigation, Writing–review and editing. FH: Conceptualization, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This work was supported by the National Natural Science Foundation of China (Grant No. 72373135); the Humanities and Social Sciences Research Project of the Ministry of Education (Grant No: 24YJAZH081).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

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