The Impact of Low-Carbon Pilot City Policy on Corporate Asset Efficiency: Evidence from China's A-Share Listed Companies

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Abstract. This study employs machine learning and the difference-in-differences (DID) approach to analyze the impact of China's "Low-Carbon City" pilot policy on the asset efficiency of A-share listed companies. The findings indicate that the policy has generally suppressed corporate asset efficiency, particularly in state-owned enterprises and large-scale companies. The study also reveals that the policy's impact is not significant in enterprises located in the eastern regions. Further robustness checks are conducted through predictive analysis using the random forest model, confirming the stability of the results. This research provides a basis for optimizing low-carbon policies and is of significant importance for promoting corporate low-carbon transformation and sustainable economic development.

Keywords: Low-carbon city pilot policy; Corporate asset efficiency; Random forest model; Difference-in-differences approach; Heterogeneous effects

1. Introduction

As the issue of global climate change continues to escalate, the urgency of addressing it has made low-carbon development an integral focus of collective concern within the international community. Among the major contributors to carbon dioxide emissions, China, as the world's largest emitter, assumes a significant role in global climate governance as it undergoes a transitional process towards low-carbon practices. In recent years, the Chinese government has proactively embarked on exploring green transformations in economic structures and energy consumption patterns through the implementation of "Low-Carbon City" pilot policies. The objective of these policies is to accomplish a substantial reduction in carbon emissions and advance sustainable development goals [1][2][3].

However, despite these efforts, the impact of the "Low-Carbon City" pilot policy on corporate asset efficiency has not received adequate attention in research. Existing literature primarily focuses on measuring corporate asset efficiency and examining the macroeconomic effects of low-carbon policies, but fails to engage in-depth discussions regarding the specific influence of the "Low-Carbon City" pilot policy on micro-level corporate asset efficiency, particularly considering enterprises of different sizes and ownership types.

To bridge this research gap, the primary objective of this study is to conduct empirical analysis that explores the impact of the "Low-Carbon City" pilot policy on corporate asset efficiency, while also examining the heterogeneous effects across various enterprise characteristics. By doing so, this research aims to contribute to the existing body of knowledge by enriching our understanding of the micro-mechanisms underlying the effects of low-carbon policies. It offers a novel perspective on how policies can shape the macroeconomy by influencing corporate-level asset efficiency.Furthermore, the practical implications of this study's findings are significant. The results will provide valuable decision-making support for further optimizing the "Low-Carbon City" pilot policy, facilitating corporate low-carbon transformations, and enhancing the overall sustainable development capabilities of the economy. With a comprehensive analysis of the impact on corporate asset efficiency, this research can aid policymakers in formulating effective strategies and measures that align with the goals of the low-carbon transition, fostering a more s resilient economic landscape.

2. Scientific background

This paper explores how the low-carbon city pilot policy affects corporate asset efficiency. It is closely related to two main streams of literature. The first is the research on corporate asset efficiency. The study of corporate asset efficiency is closely linked to asset management. [4] proposed that asset management refers to a series of activities carried out under the guidance of corporate or organizational goals. These activities are related to identifying the required assets and their funding needs, acquiring assets, providing technical support for asset maintenance systems, and managing asset renewal, all with the aim of effectively and efficiently achieving the expected goals. [5], taking fixed assets as an example, suggested that when purchasing fixed assets, one should consider their future use to improve the efficiency of departmental fixed assets. [6] believed that corporate asset quality can be evaluated from five aspects: adaptability of asset scale, structural balance, profitability, current assets, and security. [7] analyzed the reasons for the deterioration of bank asset quality and found that non-performing loans are one of the important determinants affecting the quality of bank assets.

The second stream of literature pertains to the effectiveness of "low-carbon city pilot" policies. [8], focusing on Germany, found that the implementation of low-carbon policies not only improved the air quality of the region but also reduced infant mortality rates. [9], using China as an example, found that low-carbon city pilot policies can significantly reduce carbon intensity at the city level.

Based on the above analysis, it can be seen that although existing literature has conducted extensive research on both corporate asset efficiency and the low-carbon city pilot policy, the focus on policy impact has been mostly at the macro level, with fewer studies examining how the low-carbon city pilot policy affects corporate asset efficiency. Therefore, this study intends to build on existing research, taking Chinese listed companies as the research subjects, to measure corporate asset efficiency, apply a difference-in-differences method combined with machine learning for empirical analysis, and analyze the impact of the low-carbon city pilot policy on corporate asset efficiency based on predictions of corporate asset efficiency, in order to enrich the existing literature.

This paper mainly consists of five parts. The first part is the introduction, which mainly analyzes the relationship between media attention and corporate asset efficiency. The second part is a literature review. The third part introduces the model and data sources. The fourth part is the result analysis, which mainly analyzes the results from the third part. Finally, there are conclusions and suggestions.

3. Materials and methods

3.1 Combined Weighting-TOPSIS Model

Considering the limitations of single weighting methods, this paper adopts a combination weighting method of the Analytic Hierarchy Process (AHP) and the entropy-weighting-TOPSIS, which eliminates subjective bias and objective one-sidedness. This ensures that the determined weights reflect both ubjective and objective information, thereby truly and objectively, completely and accurately reflecting the actual situation. The specific steps are as follows:

(1) Data standardization treatment.

For positive indicators: $x_{ij} = \frac{x_{ij}^{'} - \min x_j^{'}}{\max x_j^{'} - \min x_j^{'}}$; For negative indicators: $x_{ij} = \frac{\max x_j^{'} - x_{ij}^{'}}{\max x_j^{'} - \min x_j^{'}}$.

(2) Analytic Hierarchy Process (AHP)

1) Construct a hierarchical structure model: Decompose the decision-making problem into different levels, including the objective level, criterion level, and alternative level.

2) Construct a judgment matrix: At the criterion and alternative levels, compare each element pairwise and provide judgments on relative importance.

3) Perform scaling assignment: Quantify the relative importance of comparisons based on expert judgment.

4) Calculate the maximum eigenvalue of the judgment matrix: Use mathematical methods to calculate the maximum eigenvalue of each judgment matrix, and the corresponding eigenvector is the weight of each criterion or alternative.

5) Check for consistency: Calculate the consistency index of the judgment matrix to ensure the consistency of the evaluation.

6) Obtain weights: Integrate the weights at each level to obtain the total weight of the alternative level relative to the objective level.

(3) Entropy method

Calculate information entropy and determine weights: $H_j = -\frac{1}{lnn}\sum p_{ij}\ln p_{ij}$, where $p_{ij} = \frac{x_{ij}}{\sum x_{ij}}, 0 \le H_j \le 1$.

(4) Combined weighting

Calculate the comprehensive weight of the indicators: $W_j = \frac{\sqrt{\alpha_j \beta_j}}{\sum\sqrt{\alpha_j \beta_j}}$, where α_j is the weight calculated by the AHP, β_j is the weight calculated by the entropy method.

(5) TOPSIS

1) Weight the initial indicator matrix to form a weighted decision matrix.

2) Use the TOPSIS method to determine the positive ideal solution (Z+), and the negative ideal solution (Z-): $Z^+ = \{\max Z_{i1}, \max Z_{i2}, \ ...\ , \max Z_{im}\}, Z^- = \{\min Z_{i1}, \min Z_{i2}, \ ...\ , \min Z_{im}\}$.

3) Calculate the Euclidean distance of alternative i from the positive and negative ideal solutions: $D_i^+ = \sqrt{\sum(\max Z_{ij} - Z_{ij})^2}$; $D_i^- = \sqrt{\sum(\max Z_{ij} - Z_{ij})^2}$

4) Calculate the relative closeness to obtain the asset efficiency evaluation index: $Efficiency_i = \frac{D_i^-}{D_i^+ + D_i^-}$

3.2 Random Forest Prediction Model

The Random Forest prediction model not only reduces overfitting but also possesses high accuracy and robustness against outliers and missing data. Therefore, this study selects this machine learning model for the analysis, and the specific steps are as follows:

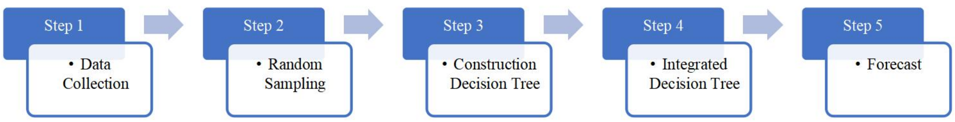

Fig. 1 Random Forest Model Prediction Steps

The low-carbon city pilot policy is an important initiative to promote sustainable development of enterprises in China. For pilot cities, they are influenced by multi-period policy shocks during the sample study period. To evaluate the policy effect, this study follows the setup of Li et al. (2016), establishing an experimental group and a control group, and separates the time differences and differences before the policy shock between the two groups through differencing, thereby obtaining the "treatment effect" of the relatively exogenous policy shock. The specific model setting is as follows:

$$y_{it} = \alpha + \beta DID_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

In the aforementioned model, the subscript i denotes the individual entity, and t denotes time. y_{it} is the dependent variable, representing corporate asset efficiency; the core explanatory variable DID_{it} is a dummy variable indicating whether city i in year t is a "low-carbon city" pilot, taking the value of 1 if included, and 0 otherwise. The control variables are set the same as mentioned above, μ_i represents the city fixed effect, λ_t represents the year fixed effect, and ε_{it} represents the random error term.

3.4 Data Sources

This paper takes A-share listed companies as the research sample, which mainly includes enterprise-related data and "low-carbon city pilot" policy-related data. On the one hand, enterprise-related data mainly comes from CSMAR, and at the same time, indicators related to corporate governance, social governance, and corporate social environmental responsibility in the asset efficiency evaluation index system come from the Bloomberg ESG evaluation index database.

4. Results and Analysis

4.1 Random Forest Prediction Results

The following figures illustrate the results of predicting corporate asset efficiency using the random forest model, where Figure 2 shows the comparison between the predicted results and actual values of the training set, and Figure 3 shows the comparison between the predicted results and actual values of the test set. It can be seen that whether it is the training set or the test set, the actual values and predicted values are very close, indicating that the random forest model used in this paper has relatively good predictive results.

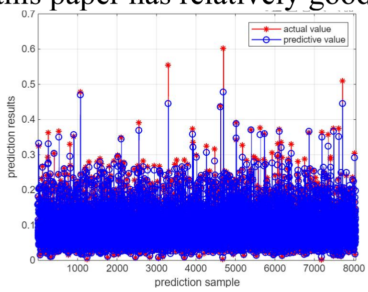

Fig. 2 Results Comparison of Training Set

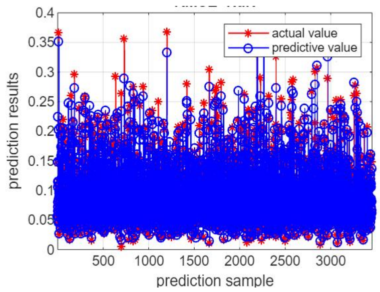

Fig. 3 Results Comparison of Testing Set

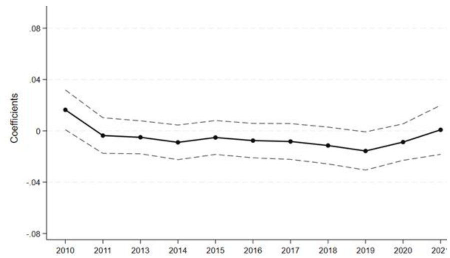

Fig. 4. Common trend

4.2 Baseline Regression Results

Table1 presents the baseline regression results of the impact of the low-carbon city pilot policy on corporate asset efficiency. In column (1), no control variables are included. Columns (2) to (4) progressively incorporate control variables related to corporate characteristics, ownership characteristics, and executive characteristics. Taking column (4) as an example, the coefficient in front of the core explanatory variable is significantly negative at the 5% level, indicating that the low-carbon pilot city policy has a significant inhibitory effect on the improvement of corporate asset efficiency.

Table 1. Baseline Regression

	Independent Variable: Asset Efficiency					
	(1)	(2)	(3)	(4)	(5)	(6)
did	-0.002	-0.004	-0.004	-0.008**	-0.008**	-0.008*
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Controls_Firm	No	Yes	Yes	Yes	Yes	Yes
Controls_Sharehol	No	No	Yes	Yes	Yes	Yes

d						
Controls_Manager	No	No	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.117***	-0.069*	-0.078**	-0.129**	Yes	Yes
	(0.001)	(0.039)	(0.039)	(0.056)	4090	4481
Observation	11485	10534	10534	4481	0.459	0.512
R-square	0.482	0.497	0.498	0.513	5.430***	13.05***
F-value	0.673	11.447***	6.034***	13.978***	-0.008**	-0.008*

Notes:Standard Errors are in the parentheses* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3 Robustness Checks

4.3.1 Parallel Trends Test

A necessary step in using the difference-in-differences (DID) model is to conduct a parallel trends assumption test. Therefore, this study, following the approach of [11] and [12], employs an event study analysis to examine the dynamic effects of the low-carbon city pilot policy. Based on the baseline model, this study specifies the following equation:

$$y_{it} = \alpha_0 + \sum_{k=-m}^{k=n} \beta_k A_k + \theta X_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \qquad (2)$$

Where A_k is a dummy variable for the year of the policy shock, k takes negative values indicating k years before the policy shock and positive values indicating k years after the policy shock. To consider the issue of multicollinearity, this study sets the year before the policy shock as the base group, and the specific results are shown in the figure. It can be seen that before the implementation of the policy, the coefficients are not significant, indicating that the experimental group and the control group have the same trend, which meets the basic premise of DID.

4.3.2 Additional Robustness Checks

To further verify the robustness of the baseline regression results, this paper also conducted additional robustness checks, with specific results shown in Table 1. Column (5) presents the results after changing the method of calculating the dependent variable, and column (6) shows the results after trimming the top and bottom 1% of the control variables. It can be observed that the coefficient in front of the core explanatory variable remains significantly negative at the 10% level, and the magnitude is not significantly different from the baseline regression results, thereby demonstrating the robustness of the baseline regression in this paper.

4.4 Heterogeneity of Corporate Ownership

To investigate the impact of the "low-carbon city pilot" policy on corporate asset efficiency, this study conducts a division of the sample based on different types of corporate ownership, specifically distinguishing between state-owned enterprises and non-state-owned enterprises. The regression results pertaining to this division are presented in columns (1) and (2) of Table2.

The analysis reveals that the "low-carbon city pilot" policy exhibits a significant inhibitory effect on corporate asset efficiency for both state-owned and non-state-owned enterprises. However, the impact is notably greater for state-owned enterprises. These findings suggest that the policy has a more pronounced influence on the asset efficiency of state-owned enterprises compared to their non-state-owned counterparts.

By conducting this division and presenting the regression results, the study provides valuable insights into the heterogeneous effects of the "low-carbon city pilot" policy based on corporate ownership. This information contributes to a more nuanced understanding of how the policy interacts with different types of enterprises and highlights the specific challenges and opportunities faced by state-owned enterprises in achieving improved asset efficiency.

4.5 Heterogeneity of Corporate Scale

Secondly, to explore how the scale of enterprises affects the impact of the "low-carbon city pilot" policy on corporate asset efficiency, this paper divides the sample into large enterprises and small enterprises based on total asset size. The regression results are shown in columns (3)-(4) of Table 2. It can be seen that the negative impact of the "low-carbon city" pilot policy on corporate asset efficiency is not significant in small enterprises, but it is significant at the 5% level in large enterprises. There are mainly two reasons: on one hand, large enterprises have a broader product market and may be subject to higher expectations and pressures from consumers and the market for green products, which requires them to adopt stricter environmental protection measures in product design and production processes, potentially increasing corporate costs; on the other hand, large enterprises, due to their important position in the economy, may be subject to stricter policy supervision and higher environmental protection requirements, which may lead to higher asset costs when they comply with policy regulations.

4.6 Heterogeneity Based on the Region Where Enterprises are Located

Additionally, to investigate whether the region where an enterprise is located affects the effectiveness of the "low-carbon city pilot" policy, this paper further divides the sample into eastern, central, and western enterprise groups based on the region where the enterprises are situated. The regression results are shown in columns (1)-(2) of Table 2. The results indicate the negative impact of the "low-carbon city" pilot policy on corporate asset efficiency is not significant for the eastern enterprise. However, the impact is also not significant for both the central and western enterprise.

Table 2. Heterogenity

	Independent Variable: Asset Efficiency						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	NSOE	SOE	Small firm	Large firm	Eastern	Middle	Western
did	-0.009**	-0.028**	-0.002	-0.015**	-0.008*	-0.009	-0.002
	(0.004)	(0.014)	(0.004)	(0.006)	(0.004)	(0.010)	(0.010)
Controls_Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls_Sharehold	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls_Manager	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	4117	269	2755	1629	3319	615	539
Observation	0.511	0.624	0.494	0.564	0.519	0.533	0.509
R-square	9.758***	3.725***	7.763***	7.976***	9.760***	14.535***	3.246***
F-value	-0.009**	-0.028**	-0.002	-0.015**	-0.008*	-0.009	-0.002

Notes: Standard Errors are in the parentheses* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Conclusion

In this study, our primary focus is on A-share listed companies in China, and we employ an empirical analysis method that combines machine learning with the difference-in-differences approach. The aim is to delve deeply into the impact of the "low-carbon city" pilot policy on corporate asset efficiency. Our findings reveal that the policy exerts a significant inhibitory effect on corporate asset efficiency, and this impact demonstrates heterogeneity across different types of corporate ownership, enterprise size, and regions. Specifically, we observe that the low-carbon city pilot policy has a more pronounced impact on the asset efficiency of state-owned enterprises and large-scale enterprises, while its effect on small-scale enterprises and enterprises in the eastern regions is not statistically significant. Moreover, we employ the random forest model to accurately predict corporate asset efficiency, further validating the robustness of the low-carbon city pilot policy effect.

Based on the aforementioned findings, this paper puts forth targeted suggestions for policymakers. Firstly, policymakers should consider the differentiated impact of enterprise size and ownership types, and formulate more precise low-carbon incentives and support policies. For large-scale enterprises and state-owned enterprises, it is recommended to provide additional technical guidance and financial subsidies to alleviate cost pressures during the low-carbon transition process and enhance asset efficiency. Secondly, considering the relatively lower sensitivity of small-scale enterprises and enterprises in the eastern regions to low-carbon policies, we suggest that local governments intensify environmental awareness propaganda and education. This will enhance enterprises' understanding of the significance of low-carbon development. Simultaneously, the establishment of low-carbon technology and information sharing platforms can foster communication and cooperation among enterprises, facilitating collaborative exploration of new low-carbon development models. Lastly, we propose increasing support for the construction of low-carbon cities in central and western regions. These areas have relatively lagged behind in the development of low-carbon cities and require greater policy inclination and technical assistance. Through measures such as optimizing industrial structure, promoting the utilization of clean energy, and strengthening environmental regulation, the asset efficiency of enterprises in these regions can be effectively improved, thereby facilitating the green and sustainable development of the regional economy. By conducting this study, our aim is to provide a scientific basis for policymakers, promote the optimization and enhancement of China's low-carbon city pilot policy, and contribute to the nation's goals of attaining peak carbon emissions and achieving carbon neutrality.

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