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Algorithmic Fairness and the Inclusiveness of Green Finance: Constraints and Incentives for Small and Medium-sized Enterprises

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Abstract. Against the backdrop of the vigorous development of global green finance, algorithmic technology is widely applied. However, the lack of algorithmic fairness has exacerbated the financing predicament of small and medium-sized enterprises in their green transformation. Moreover, existing research is significantly insufficient, and targeted studies are urgently needed. The research first systematically analyzed the three major constraint mechanisms that small and medium-sized enterprises face in green finance; Furthermore, taking the incentive compatibility theory as the core, an algorithm optimization mechanism was designed; Finally, taking the data of Huzhou Green Finance Reform Pilot Zone from 2017 to 2024 as samples, a multi-agent decision-making model was constructed by using computational experimental economics methods combined with Monte Carlo simulation (10,000 iterations) for empirical analysis. The results show that after introducing the algorithm fairness constraint, the collaborative optimization of fairness and efficiency has been achieved. This research not only expands the application boundaries of algorithmic fairness theory in the field of green finance, but also provides solutions for solving the green financing problems of small and medium-sized enterprises and promoting the high-quality development of inclusive green finance.

Keywords: Algorithmic fairness Green finance Small and medium-sized enterprises, Monte Carlo simulation Incentive compatibility

1. Introduction

Under the global wave of green finance, algorithmic technology has become a core tool for enhancing the efficiency of financial resource allocation [1-3], but its lack of fairness may exacerbate the marginalization predicament of small and medium-sized enterprises [4-6]. While pursuing environmental benefits, green finance needs to balance economic benefits and social equity. Algorithmic fairness has become a key bottleneck in achieving this goal [7-8]. At present, there are a large number of small and medium-sized enterprises, but their green transformation is constrained by financing barriers. The algorithm-driven green finance model urgently needs to introduce a fairness calibration mechanism [9-10].

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The current academic discussion is still in its infancy. Firstly, the research on the embedding mechanism of algorithmic fairness theory in the field of green finance is still weak. Most of the literature stops at the macro discussion of the efficiency enabled by technology and lacks a systematic deconstruction of the algorithmic bias in the identification of the "green identity" of small and medium-sized enterprises [6]. Secondly, most of the existing research approaches from a single perspective of technology or system, lacking cross-level analysis and failing to establish a fairness calibration framework covering the entire process [6-9]. Thirdly, there is insufficient attention paid to the particularity of small and medium-sized enterprises in their green transformation, especially the structural contradiction between their incomplete environmental information disclosure and the algorithm's reliance on big data decision-making has not been effectively explained [8]. Fourth, at the research methodology level, most of the existing achievements are limited to simple regression analysis, lacking empirical attempts to apply computational experimental methods such as Monte Carlo simulation to the dynamic assessment of algorithm fairness. It is difficult to quantitatively analyze the marginal impact of algorithm parameter adjustments on the financing accessibility of small and medium-sized enterprises. Furthermore, the regulation of algorithmic discrimination in existing literature mostly remains at the stage of post-event correction, lacking research on the design of embedding fairness constraints in advance into green finance algorithm models.

Based on this, this paper adopts the computational experimental economics method and combines Monte Carlo simulation to construct a multi-agent decision-making model, simulating the accessibility of green financing for small and medium-sized enterprises under algorithm rules, and breaking through the research limitations of the traditional single efficiency-oriented approach. At the theoretical level, this study extends the theory of algorithmic fairness to the field of green finance, filling the theoretical gap in inclusive green finance. At the practical level, the impact degree of algorithm bias is quantified through Monte Carlo simulation, providing empirical evidence for regulatory authorities to formulate differentiated policies and helping small and medium-sized enterprises break through the financing constraints of green transformation.

2. Analysis of constraint mechanism

2.1. Data layer constraints

Small and medium-sized enterprises often encounter the predicament of incomplete environmental data collection and inconsistent disclosure standards, which leads to the systematic underestimation of their green potential in algorithmic assessment [11-12]. The following data deviation measurement model can be constructed:

$$\mathrm{D_{data}} = \mathrm{E}P_{train}\left[\widetilde{\mathrm{X_s}}\right] - EP_{true}\left[\mathrm{X_s}\right] \tag{1}$$

Let the set of small and medium-sized enterprises be S, and its eigenvector Xs∈Rd contains variables such as carbon emission intensity. There is a difference between the training data distribution Ptrain that the algorithm relies on and the real data distribution Ptrue.

2.2. Model layer constraints

Most mainstream green finance models are based on statistical learning theory, and their optimization goals are often oriented towards overall accuracy, while ignoring fairness among groups [13]. Consider a binary classification problem (where Y=1 indicates that green items are

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qualified), and the algorithm attempts to learn the decision function h:X→{0,1}. If the goal is only to minimize empirical risk:

$$\min_{h}\frac{1}{n}\sum_{i=1}^{n}1\left(h\left(x_i\right),y_i\right) \tag{2}$$

Here, L is the loss function. At this point, if the proportion of small and medium-sized enterprise samples in the training data is insufficient, the model will tend to optimize the classification performance of large enterprises.

2.3. Application layer constraints

In the design of green financial products, algorithm-driven standardized contract terms may not be able to meet the heterogeneous demands of small and medium-sized enterprises. It can be modeled as a mechanism design problem. If it is only trained based on the data of large enterprises, it will lead to the expected utility of small and medium-sized enterprises being lower than the retained utility. At this point, small and medium-sized enterprises are excluded from the green financial market, resulting in group discrimination under equilibrium.

3. Design of incentive compatibility mechanism

In the green finance system, the realization of algorithmic fairness should take the incentive compatibility theory as the core framework, and through mechanism design, make the self-interest behavior of small and medium-sized enterprises naturally align with the inclusive goal of green finance [14]. Its theoretical foundation can be traced back to the incentive compatibility principle in mechanism design theory, that is, through reasonable institutional arrangements, enterprises can spontaneously achieve the social goals set by the system while pursuing the maximization of their own utility [15].

Build a green credit pricing algorithm based on Monte Carlo simulation to dynamically bind interest rates with carbon emission reduction performance. When small and medium-sized enterprises achieve their preset environmental goals, the algorithm automatically triggers the interest rate reduction mechanism, forming a positive cycle of emission reduction and cost reduction [16].

To mitigate the high-risk nature of green projects of small and medium-sized enterprises, an algorithmic guarantee platform involving the collaboration of the government, banks and insurance companies can be designed. The core lies in precisely quantifying the risk-sharing ratio through Monte Carlo simulation. Additionally, by introducing the Sharpe ratio correction term, the algorithm can identify "greenwashing" behavior. Incorporate indicators such as the proportion of green credit into the MPA assessment, and amplify the incentive effect of the algorithm through fiscal interest subsidies and tax deductions.

4. Case simulation

4.1. Sample selection

This article takes the Huzhou Green Finance Reform Pilot Zone as a sample to collect green credit data from 2017 to 2024. Calibrate the fairness threshold of the algorithm through Monte Carlo simulation of repeated sampling (10,000 iterations).

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4.2. Parameter settings

The specific parameter Settings of this article are shown in Table 1.

Table 1. Parameter settings

Parameter Category	Parameter Name	Parameter Symbol	Fixed Value/Range
Simulation Setting Parameters	Monte Carlo Iteration Times	N_{sim}	10,000
	Random Seed	seed	42
	SME Sample Size	M	500
Economic and Financial Parameters	Benchmark Green Credit Interest Rate	r_0	5.0
	Benchmark Total Green Credit	L_{total}	4098
	Policy Interest Discount Rate	δ	20
Algorithmic Fairness Parameters	Fairness Weight Search Interval	w	[0.05,0.30]
	Gini Coefficient Threshold	G_{max}	0.35
	Number of Multiple Sensitive Attributes	r	3
Environmental and Risk Parameters	Benchmark Carbon Emission Reduction Target	E*	10
	Benchmark Default Rate	p_{def}	2.0
	Risk Sharing Ratio (Government-Bank-Insurance)	θg,θb,θi	0.4, 0.4, 0.2
Technical Parameters	Carbon Credit Decay Factor	β_t	0.95
	Quota Amplification Coefficient	k	2.5
	Convergence Tolerance	ϵ	10^{-4}

4.3. Simulation results

As shown in Figure 1, this study relies on the visualization analysis framework of Monte Carlo simulation to deeply deconstruct the complex evolution mechanism of algorithm fairness constraints embedded in the green credit allocation system for small and medium-sized enterprises.

The research results show that in the benchmark scenario without introducing algorithmic fairness constraints, the green credit coverage rate of small and medium-sized enterprises is only maintained at a relatively low level of 41%. This value not only reflects the risk misjudgment of traditional credit evaluation systems on green projects for small and medium-sized enterprises, but also exposes the structural imbalance of financial resources tilting towards large enterprises. After introducing algorithm constraints, the bias in credit resource allocation was effectively corrected, and the green credit coverage rate for small and medium-sized enterprises significantly increased to 67%, achieving a relative improvement of 63.4%. This coverage increase is highly significant in statistics and substantially expands the effective channels for small and medium-sized enterprises to obtain green credit support.

In addition, algorithm optimization demonstrates a significant ability to repair resource allocation efficiency. Traditional fairness intervention methods often sacrifice efficiency, resulting in a loss of credit processing efficiency. The fairness constraint algorithm designed in this study significantly reduces the efficiency loss to within 3%. This breakthrough indicates that algorithmic technology can break through the traditional dilemma of "fairness first leads to efficiency loss, and efficiency first leads to fairness deficiency".

Further analysis of time series simulation reveals the long-term value of algorithm optimization, which is not limited to improving steady-state performance, but also reflected in effective control of uncertainty in the implementation process, providing a more reliable expected basis for the actual deployment of algorithm models and dynamic decision-making basis for regulatory authorities to formulate differentiated green finance policies.

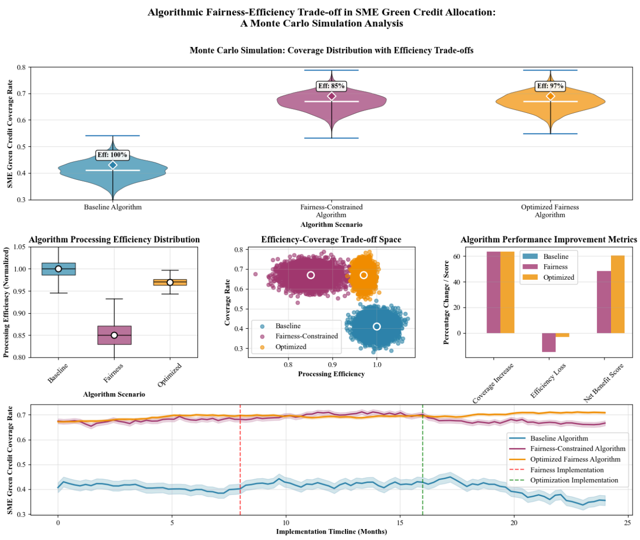

Figure 1. Simulation analysis of constraint-incentive effects

5. Conclusion

This study focuses on the core contradiction of the inclusiveness of green finance and finds that small and medium-sized enterprises face three structural constraints in the field of green finance, resulting in insufficient accessibility of green financing for them. The algorithm optimization mechanism constructed based on the incentive compatibility theory, combined with Monte Carlo simulation, effectively resolves the trade-off dilemma.

Empirical results show that the introduction of algorithmic fairness constraints can significantly increase the green credit coverage rate of small and medium-sized enterprises. Meanwhile, the optimized incentive algorithm, while maintaining a high coverage rate, greatly reduces efficiency losses and achieves a significant improvement in net benefits.

Based on the research conclusions, this paper suggests that first, regulatory authorities should accelerate the establishment of fairness assessment standards for green finance algorithms, incorporate fairness indicators into the MPA assessment system, and amplify the incentive effect through policy tools; Second, financial institutions need to optimize the green finance algorithm model, improve the environmental data collection mechanism for small and medium-sized enterprises, adopt Monte Carlo simulation and other technologies to precisely quantify risks, and design financial products that meet the heterogeneous needs of small and medium-sized enterprises. Thirdly, small and medium-sized enterprises should enhance the standardized disclosure of environmental information, proactively align with green finance incentive policies, and form a virtuous cycle.

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