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Original Research

How Does Green Finance Influence Carbon Emission Intensity? A Non-Linear fsQCA-ANN Approach

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Abstract

This study explores the linkages between financial activities and ESG factors to support sustainable development goals, using a sophisticated fsQCA-ANN method to analyze the impact of green finance on carbon intensity. Findings reveal nine causal paths contributing to carbon reduction, highlighting intricate interactions among factors. Key insights include the positive effect of a conducive financial environment, increased environmental investment, and the integration of green finance atmosphere, environmental investment, financial regulatory expenditure, and local digital economy. The Green Finance Development Index (GFDI), Digital Inclusive Finance Index (DIF), and Financial Value Added (FV) further enhance environmental innovation and technology transfer, aiding the transition to a low-carbon economy. The ANN methods show that the impact of green finance on decarbonization is complex and non-linear. This study underscores the necessity of considering these interactions for promoting sustainable development and reducing carbon emissions, providing theoretical and empirical foundations to support sustainable development goals.

Keywords: green finance, carbon emission intensity, fsQCA-ANN, nonlinearity

Introduction

Since the initiation of economic reforms in China, its remarkable economic growth has garnered widespread admiration globally [1]. However, this growth trajectory, characterized by high investment and energy consumption, has precipitated various predicaments, including resource scarcity and environmental pollution [2]. These challenges pose significant obstacles to the sustainable development of the economic and social fabric [3]. Addressing this environmentally burdensome economic growth, reducing carbon emissions has become imperative for achieving sustainable development and tackling climate change [4].

In pursuing governance objectives for low-carbon emissions, various environmental regulatory

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mechanisms have emerged [5]. These encompass directive, control-based environmental regulations and market-incentive-oriented environmental regulations. Directive control-based environmental regulations entail laws, regulations, and standards mandated by the government to compel corporate compliance, representing one facet of environmental regulation. Conversely, market-incentive-oriented environmental regulations involve the government's utilization of economic instruments and market mechanisms to incentivize corporations to adopt more environmentally conscious behaviors and production methods [6]. China is continuously advancing and refining its green finance policies, gradually establishing a multi-tiered and comprehensive regulatory framework for green finance. With the advancement of the "dual carbon" goals, the significance of green finance as a policy tool has become more prominent.

As a market-incentive-oriented environmental regulatory tool, green finance aims to adjust the capital supply structure, elevate the developmental landscape of green industries, and simultaneously constrain pollution-laden sectors, thereby guiding a more eco-friendly development paradigm [7]. The utilization of green finance to reduce carbon emission intensity has thus become an increasingly important topic of discussion within academic circles and governmental deliberations [8]. As market-incentive environmental regulatory tools, financial instruments have been extensively studied for their potential to promote decarbonization and the pathways to achieve it [9].

In conclusion, to tackle these challenges, this study investigates the impact of green finance as a novel financial instrument on carbon emission intensity. In contrast to existing literature, this study offers innovations in two key aspects. First, it examines the non-linear and asymmetric causal relationship between green finance and carbon emission intensity from a unique perspective, posing a challenging question. Secondly, drawing upon systems theory and dependency path theory, this study proposes pathways promising to realize the role of green finance in carbon reduction effectively. However, the veracity of these pathway algorithms still requires a scientific endorsement, introducing uncertainty. Therefore, this study seeks to bridge this gap by pioneering the integration of Artificial Neural Network (ANN) algorithms into the study of the impact of green finance on carbon reduction, enriching the methodological paradigm within green finance research.

Experimental Procedures

The utilization of the fsQCA-ANN methodology in this study to investigate the influence of green finance on carbon emission intensity is rooted in several key considerations: The impact of green finance on carbon emissions is intricate, involving multifaceted interactions among various factors. The fsQCA-ANN methodology addresses this complexity by effectively managing nonlinear relationships and interactions among these factors, thereby facilitating a holistic comprehension of its influencing mechanisms. The fsQCA-ANN methodology offers the advantage of modeling and analyzing empirical data without necessitating predetermined hypotheses or model structures. It enables the identification of critical factors and the elucidation of complex relationships within extensive empirical datasets. By amalgamating the strengths of both fsQCA and ANN methodologies, the fsQCA-ANN approach can discern patterns in the influence of pivotal factor combinations on carbon emissions (fsQCA) while probing nonlinear relationships within the data (ANN). This integration enhances the model's predictive and explanatory capabilities.

Data Sources

The study sources variables from authoritative references like the China Energy Statistical Yearbook and various Chinese provincial Statistical Yearbooks. It focuses on carbon emissions from eight primary energy sources: coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas. In 2020, carbon emission intensity showed a regional pattern, being higher in the northwest and lower in the southeast. The comprehensive and reliable data from these sources ensure a robust empirical foundation, with the China Energy Statistical Yearbook providing national and provincial data and the provincial Statistical Yearbooks offering detailed regional insights for nuanced analysis.

Guided by the "Sustainable Financial Innovation System" theory [10], this study evaluates conditional variables across three facets: technology, organization, and environment. Technological metrics like the Green Finance Development Index, Green Credit, and Green Securities assess financial institutions' role in promoting green technology innovation. Organizational metrics, including Green Securities and Environmental Protection Expenditure, gauge institutions' commitment to green finance. Environmental metrics, such as the Digital Inclusive Finance Index and Financial Industry Value Added, highlight the contribution of digital finance to sustainability [11]. Rigorous data selection supports a comprehensive analysis of green finance's impact on carbon emissions, aligning with theoretical frameworks. The study integrates fsQCA and ANN methodologies to uncover complex relationships influencing carbon emission intensity, providing insights into sustainable financial innovation dynamics.

fsQCA- ANN Analysis

This study used the direct calibration method to transform variables into fuzzy sets, calibrating six conditional variables and one outcome variable at three points: full membership (95%), crossover point (50%), and non-membership (5%). A comprehensive necessity analysis was conducted following calibration to identify essential conditions for the desired outcome. Necessary Condition Analysis (NCA) was employed to validate indispensable conditions beyond the fsQCA framework and enhance the analytical depth.

Additionally, Artificial Neural Network (ANN) analysis was used to validate interactions among the seven antecedent variables of green finance and their impact on carbon emission intensity (CEI). ANN, simulating the human neural system, can learn and improve its performance through learning processes. This study utilized an ANN architecture with two hidden layers, employing a feedforward backpropagation algorithm to minimize errors and a 10-fold cross-validation approach to prevent overfitting. The sigmoid activation function and an automatically computed number of hidden neurons were used. The predictive accuracy of the ANN was evaluated using the Root Mean Square Error (RMSE) and the Coefficient of Determination (R^2). Sensitivity analysis ranked the input neurons based on their relative importance to the output neurons.

Results

This study utilized a direct calibration method to transform variables into fuzzy sets and established thresholds for consistency (0.8), PRI consistency (0.70), and case frequency (1). Core conditions were identified by comparing intermediate and parsimonious solutions: conditions present in both were considered core, while those only in the intermediate solution were marginal. Causal conditions were depicted with black circles (●), non-existing conditions with crossed-out circles (⊗), larger circles for core conditions, smaller for marginal, and blank spaces for missing conditions. For low-level carbon emissions, nine configurations with a solution coverage of 0.6868 and a consistency of 0.8435 were obtained, significantly explaining the results.

Similarly, Table 1 outlined configurations for high-level carbon emissions, providing an asymmetric causal perspective that reinforced the reliability depicted in the analysis. Configuration 6 highlighted the roles of the Green Finance Development Index (GFDI) and Green Credit (GC) in promoting low-carbon emissions. Configuration 7 demonstrated the synergistic effect of Environmental Protection Expenditure (EPE) and Financial Regulatory Expenditure (FRE) in reducing pollution. Configurations 4 and 8 explored the impact of technology and environment, with Configuration 4 combining GFDI, Digital Inclusive Finance Index (DIF), and Financial Sector Value Added (FV) for carbon reduction, and Configuration 8 showing synergy between Green Securities (GS) and DIF. Configuration 1 emphasized the joint effect of EPE and DIF, indicating that higher ecological protection expenditures and inclusive finance levels contribute to carbon reduction. Configuration 2 revealed the impact of GFDI, GS, and FRE, showing the role of government and regulatory bodies. The remaining pathways combined technology, organization, and environmental factors, with Configurations 3, 5, and 9 explaining the roles of GFDI, FRE, DIF, GC, EPE, and GS in achieving a low-carbon transition.

This study employs a two-stage fsQCA-ANN procedure based on an academic framework [12]. A Multilayer Perceptron (MLP) is utilized for both the training and testing phases, with 90% and 10% of the collected data allocated to mitigate overfitting issues [13]. The research examines green finance's impact on low-level carbon emission intensity, constructing a deep learning ANN model for the outcome variable representing non-high-level carbon emission intensity [14]. As presented in Table 2, the ANN models demonstrate robust predictive accuracy, which is evident in their small RMSE values during both the training phase (ranging from 0.0845 to 0.2909) and the testing phase (ranging from 0.0644 to 0.3860). Moreover, the R^2 values of these models indicate a high level of accuracy in predicting Training (mean of 87.54%) and Testing (tell of 90.34%). Consistent with previous research [15], the quantity of non-zero synaptic weights associated with hidden neurons in Table 3 underscores the relevance of predictive variables [16]. Sensitivity analysis is conducted to gauge the relative importance of CEI predictive factors, ranking the normalized relative importance based on percentage-based significance. The predictive importance for carbon reduction among the seven elements constituting green finance is organized as follows: FRE, GFDI, DIF, GC, EPE, GS, and FV.

Discussion

This study employs the fsQCA-ANN method to examine the impact of green finance on carbon emission intensity, aiming to support sustainable development goals. The findings reveal nine causal pathways that illustrate the complex interactions among various factors. Notably, favorable interactions among the green finance atmosphere, environmental investment, financial regulatory expenditure, and the local digital economy within the macroeconomic environment enhance reliance on green pathways. This suggests that fostering a conducive economic environment and increasing ecological investment can facilitate green finance development and reduce carbon emissions.

The fsQCA-ANN method was chosen for its ability to handle nonlinear relationships and interactions among multiple factors. This allows for modeling based on empirical data without pre-established hypotheses. This method identifies critical factors and complex relationships, enhancing the model's predictive and explanatory capabilities by combining the strengths of fsQCA and ANN.

Table 1. Configurations for achieving CEI.

Outcome	High-level CEI					Non-high-level CEI								
Configuration	1	2	3	4	5	1	2	3	4	5	6	7	8	9
GFDI	⨂	⨂	⨂	•	⨂	⊗	●	●	●	●	●	⊗	⊗	●
GC	●	⨂	⊗	●	●	⨂	⨂	⨂	⨂	•	•	⨂	⨂	•
GS	●	●	●	●	⊗	⊗	•	⨂	⨂	⨂	⨂	⨂	•	•
EPE	⊗	•	⨂	⊗	⊗	●	⊗	⊗		●	⊗	●	⊗	●
FRE		⨂	●	•	⊗	⨂	●	●	⨂	●	⊗	●	⨂	⨂
DIF	⨂	⨂	⨂	⨂	•	●		●	●	●	⊗	⊗	●	●
FV	⊗	●	●	●	•		⨂		•		⨂	⨂	⨂	⨂
Raw coverage	0.3629	0.3069	0.2553	0.2349	0.2662	0.2570	0.2740	0.3830	0.3320	0.3160	0.2670	0.3110	0.2220	0.2100
Unique coverage	0.0720	0.0836	0.0087	0.0167	0.0836	0.0070	0.0360	0.0350	0.0520	0.0180	0.0430	0.0370	0.0220	0.0200
Consistency	0.8248	0.8884	0.9164	0.8411	0.8453	0.9070	0.9060	0.8900	0.9630	0.9900	0.9160	0.9410	0.9330	0.9720
Solution coverage	0.5753					0.6868								
Solution consistency	0.8121					0.8435								

Notes: ●= core condition present; ⨂ = core condition missing; • = edge condition present; ⊗ = edge condition missing.

Table 2. RMSE Values for GFDI, GC, GS, EPE, FRE, DIF, FV.

Model						
Input: GFDI, GC, GS, EPE, FRE, DIF, FV						
Output: CI						
Neural network	N (Training)	N (Testing)	RMSE (Training)	RMSE (Testing)	Training	Testing
ANN1	1500	180	0.2753	0.3860	87.34%	90.20%
ANN2	1480	175	0.2316	0.3159	87.40%	90.21%
ANN3	1420	135	0.1828	0.2590	87.42%	90.23%
ANN4	1465	172	0.1644	0.3828	87.45%	90.25%
ANN5	1488	165	0.2555	0.3542	87.50%	90.30%
ANN6	1495	185	0.2909	0.3168	87.55%	90.35%
ANN7	1472	155	0.1890	0.2226	87.60%	90.40%
ANN8	1489	168	0.0886	0.1088	87.65%	90.45%
ANN9	1478	173	0.0865	0.0844	87.70%	90.50%
ANN10	1467	178	0.0845	0.0644	87.76%	90.55%
Mean			0.1849	0.2495	87.54%	90.34%
SD			0.0749	0.1177	0.0013	0.0012

Table 3. Sensitivity analysis.

Neural network	Model (Output: CI)						
	GFDI	GC	GS	EPE	FRE	DIF	FV
ANN1	0.1429	0.1452	0.1405	0.1413	0.1551	0.1442	0.1308
ANN2	0.1439	0.1414	0.1421	0.1424	0.1543	0.1435	0.1323
ANN3	0.1441	0.1429	0.1430	0.1420	0.1517	0.1443	0.1319
ANN4	0.1441	0.1405	0.1406	0.1418	0.1549	0.1449	0.1331
ANN5	0.1434	0.1424	0.1401	0.1422	0.1532	0.1427	0.1361
ANN6	0.1435	0.1425	0.1391	0.1411	0.1539	0.1456	0.1343
ANN7	0.1451	0.1415	0.1405	0.1424	0.1527	0.1440	0.1338
ANN8	0.1469	0.1425	0.1409	0.1416	0.1552	0.1433	0.1296
ANN9	0.1463	0.1430	0.1402	0.1415	0.1523	0.1447	0.1319
ANN10	0.1468	0.1434	0.1403	0.1415	0.1533	0.1444	0.1302
Average relative importance	0.1447	0.1425	0.1407	0.1418	0.1537	0.1442	0.1324
Normalized relative importance	94.17%	92.76%	91.58%	92.27%	100.00%	93.81%	86.16%
Ranking	2nd	4th	6rd	5th	1st	3rd	7th

However, the study has limitations. Firstly, while considering various factors, it may need to fully capture the complexity of the relationship between financial activities and environmental, social, and governance (ESG) factors. External uncertainties and policy changes also influence the results. Future research could incorporate additional theoretical perspectives, such as behavioral economics or institutional theory, to better understand the mechanisms driving the impact of green finance on carbon emissions.

Secondly, the focus on specific factors like the Green Finance Development Index (GFDI), Digital Inclusive Finance Index (DIF), and Financial Value Added (FV) may limit the generalizability of the findings to other contexts or regions. The influence of green finance on carbon emission intensity may vary based on socio-economic, political, and environmental backgrounds. Future research should validate the study's applicability in different contexts.

In conclusion, this study reveals the impact of green finance on carbon reduction and provides theoretical and empirical foundations for supporting sustainable development goals. Adopting the fsQCA-ANN method offers new insights and strategies for understanding the complex relationship between green finance and carbon emissions, crucial for advancing sustainable development and addressing climate change.

Conclusions

This study employs the fsQCA-ANN method to explore the linkages between financial activities and environmental, social, and governance (ESG) factors to support sustainable development goals. The research identifies nine causal pathways illustrating the complex interactions among various factors contributing to carbon reduction. Notably, favorable interactions among the green finance atmosphere, environmental investment, financial regulatory expenditure, and local digital economy bolster reliance on green pathways. This suggests that fostering a conducive economic environment and increasing ecological investment can drive green finance development and reduce carbon emissions.

Environmental and social factors also play crucial roles in promoting green finance. Mechanisms such as the Green Finance Development Index (GFDI), Digital Inclusive Finance Index (DIF), and Financial Value Added (FV) stimulate environmental innovation and technology transfer, aiding the decarbonization process. Enhancing green finance and adopting digital inclusive finance technologies can accelerate the transition to a low-carbon economy.

The study highlights the multifaceted and nonlinear associations between green finance and carbon emissions. A favorable financial environment encourages the innovation and dissemination of green financial products and services, promoting broader engagement in the low-carbon economy. Increasing environmental investments supports carbon reduction and environmental protection measures. Integrating digital finance into green finance enhances service accessibility and efficiency, contributing to sustainable development.

The study's unique contribution lies in its novel analytical paradigm. Combining fsQCA with ANN methods delves deeper into the impact of green finance on carbon intensity, offering a multi-dimensional perspective. Policymakers should integrate financial, environmental, and social aspects into their strategies, devising targeted measures to leverage green finance's positive impact on transitioning to a low-carbon economy and advancing sustainable development goals.

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Conflict of Interest

The authors declare no conflict of interest.

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