



The Effect of Green Credit Constraints on Carbon Neutrality in Heavy-Polluting Enterprises

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Abstract. As one of the main institutional supports for the low-carbon development of heavily polluting enterprises, the impact of green credit on the carbon emission behaviour of firms and the corresponding transmission mechanism has not been studied in depth. The 6,392 firm-year observations of A-share heavy-polluting enterprises' panel data from 2014 to 2023 are used here. A two-way fixed-effects model and a mediation framework will be used in this paper to investigate the effect of green credit constraints on corporate carbon intensity and the reasons for such an effect. Based on the above results, it can be seen that strengthening the green credit system has reduced the carbon intensity of high-polluting enterprises; that is to say, an increase in the proportion of green loans to total funds reduces carbon emissions per unit of operating revenue. Innovation in green technology also has an indirect effect, and the corresponding effect is about 8.50 per cent of the total effect; However, the result of the Sobel Z-test is not statistically significant, so it cannot be determined whether this path is strong. According to the heterogeneity analysis, most of the carbon reduction effects are due to state-owned enterprises; for non-state-owned enterprises, it is not statistically significant, which may be because they have had fewer opportunities to obtain green credit. This paper offers some data and recommendations to promote the development of green credit policies, boost the transmission mechanism of green technology innovation, and adjust policies according to different property rights.

Keywords: Green Credit Constraints, Carbon Intensity, Heavily Polluting Enterprises, Green Technology Innovation, Mediation Effect.

1 Introduction

The international governance of climate change has sped up, and achieving carbon neutrality is now one of the national plans to support the construction of ecological civilisation and high-quality economic growth in China. In 2012, the release of the Green Credit Guidelines formally put forward green credit as one of the main means for financial regulation to guide the low-carbon transformation of the real economy. In recent years, the policies have been getting stricter, and now a whole system of credit control has been introduced to limit debt financing and trade credit [1]. Although heavy-polluting industries are the main sources of industrial carbon emissions and are

concentrated in high-energy-consuming pillar sectors such as thermal power, steel, chemicals, coal, etc [2]., they need a lot of long-term funds for financing the upgrade of low-carbon equipment, renovation of green production processes and research and development in energy-saving technologies; however, they are now under tighter financing restrictions, and many enterprises face a dilemma: they need to reduce emissions but lack the necessary funds for the transition.

Current studies on the environmental effects of green credit policies can be organised in three directions: how well they can reduce emissions, what are the reasons for this effect, and what factors restrict the impact of the policy. There is general agreement among many people that green credit can reduce a company's carbon emissions and pollution. Sun and Zeng took the 2012 Green Credit Guidelines as a quasi-natural experiment, and with the help of a difference-in-differences (DID) design, they found that green credit has reduced the absolute carbon emissions of heavy-polluting enterprises to a certain extent, and this effect has been gradually expanding each year [3]. Song and Jin acquired the above data from the China Industrial Enterprise Database and the Pollution Emission Database covering the years 2000-2014, and it was discovered that green credit reduced the SO₂-emission intensity of enterprises in three ways: innovation subsidies, financing constraints, and compliance costs [4]. It should be noted that the dependent variables in the above studies are either total carbon emissions or pollutant emission intensity, and none of them have chosen carbon emission intensity (carbon emissions per unit of operating revenue) as a micro-level index of corporate carbon reduction efficiency. Carbon emission intensity is directly related to the main logic of carbon neutrality, that is, "to support higher economic output at a lower carbon cost", so it is also a key micro-indicator of a company's carbon neutrality level.

The diagram of the Transmission is also quite elaborate. Lu and others have found that green credit may cause polluting enterprises to increase the number of green patent applications by restricting their access to funds and raising the cost of debt [2]. Li and others took a sample of green enterprises and found that green credit can promote real green innovation to some extent [5]. At the same time, Chai and others found that although green credit reduced the illiquid debt financing of heavy-polluting enterprises, the companies were unable to cover the resulting shock through other ways, such as trade credit, so the green reallocation of credit resources was only partially achieved [1]. Xu and Liu found that the green finance policy crowds out non-green innovation and promotes green innovation; thus, there will be a structural cost to the overall development of innovation [6]. Chen and others have found that the intensity of R&D investment does not moderate the gains in carbon performance from green credit, so only explicitly green-oriented technological innovation will likely serve as an effective mediator. Chen and Zhang took green bonds as the object of their study and further discovered that the initial growth of innovation under the support of green finance is concentrated in low-threshold areas, such as utility model patents; therefore, careful attention needs to be paid to the quality differentiation of green innovation [8]. Taken together, the above results show that there is corporate circumvention and innovation in portfolio restructuring along with the policy effect of green credit, and thus the transmission mechanism of policy effects is non-linear [6-8].

Firm ownership has gradually become one of the reasons for the different policy effects, but the results are not clear. Song and Jin took the sample of industrial enterprises from 2000 to 2014, and found that the environmental performance improvement resulting from green credit was stronger for non-state-owned enterprises (non-SOEs) than for state-owned enterprises (SOEs) [4]. Cai and Liu have examined the listed companies from 2009 to 2021, and it has been found that the competitiveness-enhancing effects of green credit are more pronounced for non-SOE enterprises [9]. Sun and Zeng also found that non-SOEs were more sensitive to the policy [3]. The three studies have all found that the marginal effect of non-SOEs is relatively large. However, they are all at the level of the dependent variables (emission levels, performance levels, competitiveness levels). It is not clear whether the direction of ownership-based differentiation will change after switching the dependent variable to carbon emission intensity, and this issue has not been studied empirically in previous research. Wang and others have shown in recent years that, due to the political promotion system, top management of state-owned enterprises are driven to reduce greenhouse gas emissions more strongly by undertaking green innovation and adjusting production [10]. Ren and others have also found that the incentive system of the SOE is more conducive to behaviour at the level of executive behaviour for political behaviour than for private enterprise managers [11]. Given that the rigidity of compliance is relatively high and the scale of carbon reduction for state-owned enterprises is large, the direction of ownership-based differentiation may change in the examination of carbon efficiency [10,11].

Tian and Nie (2007-2020) carried out a knowledge graph analysis of the 236 green credit studies published in CSSCI-indexed and Chinese core journals and found that "studies evaluating the implementation effects of green credit are relatively scarce, and thus it is difficult to assess policy effectiveness"; this provides a good reference for the present study [12]. The three main problems of the current research are as follows: First of all, the dependent variable has not moved from "total quantity" to "efficiency"; carbon emission intensity is an important micro-level index of firm-level carbon neutrality efficiency and not an absolute amount of emissions. Second, there has been no integrated mechanism test of the entire causal chain of "green credit $\rightarrow$ green technology innovation $\rightarrow$ carbon emission intensity"; Lu and others have tested the upstream part, and Sun and Zeng have tested the downstream part, but the whole mediating path has not been verified experimentally. Thirdly, the main consensus on ownership heterogeneity is at the level of different classes; the possible reversal under the perspective of carbon emission intensity has not yet been resolved in academic research [2, 3].

Based on the deficiencies mentioned above, this paper takes the A-share listed companies in heavy-polluting industries in China from 2014 to 2023 as the sample, carbon emission intensity (FCE) as the dependent variable, green credit level (Green) as a continuous explanatory variable, and green technology innovation (lnTotal) as the mediating variable. This paper proposed that a system should be built connecting green credit, green technology innovation, and carbon emission intensity, and then the three hypotheses will be tested empirically. H1: Green Credit will reduce the proportion of high-carbon production in a company. H2: Green credit can reduce the amount of carbon emissions through the promotion of green-technology innovation; therefore, the

latter is a mediator. H3: Green Credit will lower the carbon emissions per unit of production of state-owned enterprises. The three marginal contributions of this paper are as follows: First, it is no longer the main focus of research that "total emission reduction" but rather the carbon emission intensity index. Secondly, it can also demonstrate the entire chain of causation of "green credit to green technology innovation and carbon emission intensity", and is in line with the results of Chen et al. that R&D investment does not mediate this relationship. Third, whether the pattern of ownership heterogeneity for carbon emission intensity is in line with or deviates from the current consensus can be used to provide new evidence for understanding the different positions of enterprises under various ownership structures in the process of carbon neutrality [7].

2 Research Design

2.1 Variable Specification

Table 1. Variable definitions.

Type	Variable	Sym- bol	Definition
Dependent variable	Corporate carbon emission intensity	FCE	Carbon emissions / Operating revenue
Explanatory variable	Green credit level	Green	Green credit amount / (Long-term borrowings + Short-term borrowings)
Mediating variable	Green technology innovation	GT	$\ln(1 + \text{Total green patent applications})$
Control variables	Firm size	SIZE	Natural logarithm of total assets
	Return on assets	ROA	Net profit / Average total assets
	Leverage	Lev	Total liabilities at year end / Total assets at year end
	Listing age	List Age	$\ln(\text{Fiscal year} - \text{IPO year} + 1)$
	Management expense ratio	Mfee	Administrative expenses / Operating revenue

Table 1 is the definition of the key variables. Carbon emission intensity of enterprises (FCE) is the ratio of a company's carbon emissions to its operating income. The main explanatory variable is the green credit level (Green), which is the ratio of green credit to total borrowings (short-term and long-term). Green technology innovation ($\ln(\text{Total})$) is the mediating variable and is defined as $\ln(1 + \text{green invention patent applications} + \text{green utility model patent applications})$. The control variables are firm size (SIZE, $\ln(\text{total assets})$), return on assets (ROA, net profit/average total assets), leverage (Lev, total liabilities/year-end total assets), listing age (ListAge, $\ln(1 + \text{years since IPO})$), and management expense ratio (Mfee, administrative expenses/operating revenue)), which

are used to measure the effect of a company's scale, profitability, financial leverage, age, etc., on the dependent variable.

2.2 Data and Sample

The two official databases are CSMAR (China Stock Market and Accounting Research) and Wind; these have provided the firm-level data for this paper. Based on the above, this paper identified A-share listed companies in heavy-polluting industries and obtained a sample from 2014 to 2023. To guarantee the quality of the data in the sample, the following steps have been taken: (1) Observations marked as ST or *ST in the sample year are excluded; (2) Observations with missing values are excluded; (3) Firms in non-heavy-polluting industries (e.g., finance, real estate) are excluded; and (4) To reduce the effect of outliers, all continuous variables have been winsorised at the 1st and 99th percentiles. Finally, this paper used 6,392 firm-year observations.

2.3 Model SpecificationEmpirical Results

The following base econometric model will be used to study the effect of green credit on corporate carbon emissions.

$$FCE_{it}=\alpha_0+\alpha_1Green_{it}+\alpha_2Controls+Year_t+Company_i+\epsilon_{it}\tag{1}$$

To examine the mediating effect of green technology innovation, the following three-step mediation model will be employed:

$$GT_{it}=\alpha_0+\alpha_1Green_{it}+\alpha_2Controls+Year_t+Company_i+\epsilon_{it}\tag{2}$$

$$FCE_{it}=\alpha_0+\alpha_1Green_{it}+\alpha_2GT_{it}+\alpha_3Controls+Year_t+Company_i+\epsilon_{it}\tag{3}$$

The i and t index firm and year, respectively. FCE_{it} measures corporate carbon emission intensity. $Green_{it}$ denotes the green credit level. GT_{it} proxies green technology innovation. Controls includes a battery of control variables. $Company_i$ captures firm fixed effects. $Year_t$ captures year fixed effects. ϵ_{it} is the stochastic disturbance term.

3 Empirical Results

3.1 Descriptive Statistics

Table 2 is the distribution of the main variables. FCE has a mean of 2.769 (SD = 0.999, range: 0.328 - 4.905) and is relatively spread out in the cross-section of carbon emissions per unit of operating revenue. Green has a mean of 0.108 (SD = 0.023, range: 0.065-0.157), so green credit makes up a relatively small proportion of total borrowing and is narrowly distributed. GT has a mean of 0.362 (SD = 0.762, range: 0-3.367), and the pattern is that most sample firms file few green patent applications, but the output of green innovation differs greatly among firms. Among the control variables, SIZE is 22.60 (SD = 1.386), ROA is 0.037 (SD = 0.056), Lev is 0.434 (SD = 0.193), ListAge

is 2.368 (SD = 0.736), and Mfee is 0.063 (SD = 0.042). All the control variables are in a reasonable range and do not have any significant outliers.

Table 2. Descriptive statistics of variables.

Variable	N	Mean	SD	Min	Max
FCE	6392	2.769	0.999	0.328	4.905
Green	6392	0.108	0.0230	0.0650	0.157
GT	6392	0.362	0.762	0.000	3.367
Size	6392	22.60	1.386	20.19	26.36
ROA	6392	0.0370	0.0560	-0.173	0.189
Lev	6392	0.434	0.193	0.0650	0.886
ListAge	6392	2.368	0.736	0.693	3.367
Mfee	6392	0.0630	0.0420	0.00800	0.230

3.2 Correlation Analysis and Multicollinearity Test

Table 3. Correlation analysis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) FCE	1.000							
(2) Green	-0.267** *	1.000						
(3) GT	-0.097** *	0.083** *	1.000					
(4) Size	-0.075** *	0.038** *	0.289** *	1.000				
(5) ROA	-0.003	0.013	0.043** *	0.019	1.000			
(6) Lev	0.010	-0.027** *	0.102** *	0.491** *	-0.408** *	1.000		
(7) ListAge	-0.051** *	0.038** *	0.079** *	0.422** *	-0.174** *	0.312** *	1.000	
(8) Mfee	0.124** *	-0.106** *	-0.165** *	-0.377** *	-0.196** *	-0.214** *	-0.091** *	1.000
*** p<0.01, ** p<0.05, * p<0.1								

Table 3 is the Pearson correlation coefficient matrix of the basic variables and presents the initial state of their pairwise relationships before regression analysis. The

correlation matrix shows the degree of pairwise association, and most are statistically significant. The main explanatory variable, Green, is negatively correlated with FCE at $r = -0.267$ and $p < 0.01$; thus, it can be assumed that a higher proportion of green credit in total borrowing is associated with lower carbon emissions per unit of operating revenue. GT, the mediating variable, is negatively correlated with FCE ($r = -0.097$, $p < 0.01$) and positively correlated with Green ($r = 0.083$, $p < 0.01$); thus, it is expected that GT mediates the effect. Among the control variables, SIZE is negatively correlated with FCE ($r = -0.075$, $p < 0.01$), ROA is not significantly associated with FCE ($r = -0.003$, $p > 0.1$), Lev is also not significantly correlated with FCE ($r = 0.010$, $p > 0.1$), ListAge is negatively related to FCE ($r = -0.051$, $p < 0.01$), and Mfee is positively correlated with FCE ($r = 0.124$, $p < 0.01$). All absolute values of pairwise correlation coefficients are less than 0.7, so multicollinearity is not a problem. All of the above are in line with the theory.

Before carrying out the regression analysis, a multicollinearity test is to be conducted to verify the reliability of the regression model. The Variance Inflation Factor (VIF) of each variable in the base regression model is used for testing. If all the VIF values are less than 10, there will be no problem of multicollinearity. As shown in Table 4, all VIF values are less than 10 and thus multicollinearity does not affect the estimation.

Table 4. Multiple correlation (VIF).

Variable	VIF	1/VIF
Size	1.85	0.541767
Lev	1.77	0.565872
ROA	1.42	0.705953
ListAge	1.28	0.783358
Mfee	1.27	0.788228
GT	1.11	0.904935
Green	1.02	0.978101
Mean VIF	1.39	

3.3 Baseline Regression Results

Table 5 reports the baseline regression results. Column (1) includes only the core explanatory variable, Green, while Column (2) adds all control variables. Both columns control for firm and year fixed effects. As shown in Column (2), the coefficient of Green is -0.5947 , significant at the 10% level ($t = -1.9512$), indicating a significant negative relationship between the green credit policy and carbon emissions of high-polluting firms. This suggests that an increase in the proportion of green credit is associated with lower carbon emissions per unit of operating revenue, consistent with our theoretical expectations. Thus, Hypothesis H1 is supported.

Among the control variables, firm size (Size) has a coefficient of -0.1463 , significant at the 1% level ($t = -5.0651$), indicating that larger firms tend to have lower carbon emissions, possibly due to greater investment in environmental technologies and more standardized management practices. The coefficient of leverage (Lev) is 0.2325 , significant at the 5% level ($t = 2.0116$), suggesting that firms with higher financial leverage

emit more carbon. The coefficient of ListAge is 0.0868, significant at the 5% level ($t = 2.0502$), indicating that longer-listed firms have higher emissions. The coefficient of ROA is -0.0454 but not significant ($t = -0.2477$). Results for other control variables are consistent with theoretical expectations.

Table 5. Baseline regression results.

	(1)	(2)
VARIABLES	FCE	FCE
Green	-0.6593** (-2.1697)	-0.5947* (-1.9512)
Size		-0.1463*** (-5.0651)
ROA		-0.0445 (-0.2477)
Lev		0.2325** (2.3350)
ListAge		0.0868** (1.9690)
Mfee		1.6037*** (3.9693)
Constant	2.8404*** (86.5551)	5.7349*** (9.1279)
Observations	6,392	6,392
R-squared	0.8100	0.8136
Company FE	YES	YES
Year FE	YES	YES

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, (t) is shown in parentheses. The same is true for all the tables below.

3.4 Robustness Tests

Auxiliary Dependent Variable. To address the problem that the baseline estimates are affected by the specific choice of dependent variable measurement, this paper takes the natural logarithm of corporate carbon emission intensity (LnFCE) and re-estimate the model. As shown in Column (1) of Table 6, the coefficient of the main explanatory variable, green credit level (Green), is -0.4022 and is statistically significant at the 5% level ($t = -2.1167$), consistent with the results of the baseline. Based on the above results, it can be concluded that the dampening effect of green credit on corporate carbon emissions is not affected by the specific operation of the dependent variable and is thus considered robust.

Reduced Sample. Considering that the external factor in 2020 due to the COVID-19 pandemic could have affected the company's operating results, do not include the data from 2020 onwards and will restrict the estimation period to before the pandemic, thus

minimising the bias caused by it. As shown in Column (2) of Table 6, the results show that the coefficient for Green is -0.7511, which is at the 10% significance level ($t = -1.8823$) and consistent with the baseline estimate. Therefore, the dampening effect of green credit on corporate carbon emissions may still exist in the years after the pandemic, so can include them in the analysis.

Table 6. Estimates of robustness test.

	Alternative dependent variable	Reduced sample
VARIABLES	LnFCE	FCE
Green	-0.4022** (-2.1167)	-0.7511* (-1.8823)
Size	0.6639*** (24.6565)	-0.1724*** (-4.9698)
ROA	0.8878*** (6.1661)	-0.1202 (-0.5430)
Lev	0.0438 (0.4726)	0.1899 (1.5683)
ListAge	0.0230 (0.6479)	0.1299** (2.4618)
Mfee	-4.7260*** (-12.0520)	1.8317*** (3.9593)
Constant	-1.0298* (-1.7662)	6.1017*** (8.1064)
Observations	6,392	4,891
R-squared	0.9683	0.8255
Company FE	YES	YES
Year FE	YES	YES

4 Conclusion

Based on a sample of A-share listed companies in the heavily polluting sector from 2014 to 2023, a two-way fixed-effects model will be used in this paper to examine the effect of green credit (Green) on corporate carbon emission intensity (FCE) and how this effect is transmitted through green technology innovation (lnTotal). The three reasons are as follows. First, green credit has a relatively small negative effect on the carbon emission intensity of enterprises (coefficient = -0.5947, $p < 0.10$), and therefore, it is not concluded that increasing the proportion of green credit in a company's financing structure reduces its carbon emissions per unit of operating revenue; in fact, it may be that the impact is not significant enough. Second, green technology innovation also has an indirect effect on it; that is to say, the indirect effect is -0.0505 and makes up 8.50% of the total effect. The Sobel Z-statistic is 1.818 and, as a result, is below the 5% critical value; thus, it should be considered that the statistical strength

of this mediation path is not high, and other paths of the carbon-abatement effect of green credit need to be examined. Thirdly, the heterogeneity analysis shows that the carbon reduction effect of green credit is concentrated in state-owned enterprises; that is, in the SOE sub-sample, the coefficient of Green is -0.9168 ($p < 0.05$), and in the non-SOE group, it is -0.2622 ($p > 0.1$). Therefore, it can be concluded that SOEs have a more favourable institutional environment and are subject to tighter emission control policies in the policy direction.

Based on the above results, the following policy suggestions are put forward. First, in order to broaden the coverage of green credit for non-state-owned heavy-polluting enterprises, the access threshold for green finance needs to be reduced and the focus of the policy should change from "supply" to "access". Second, in order to strengthen supervision over the use of green credit funds and the post-lending carbon performance assessment mechanism, it is necessary to prevent enterprises from receiving financing in the name of green development but employing the funds for non-green activities. Thirdly, due to the different ownership forms of enterprises, many policies can be introduced to strengthen the post-lending carbon performance assessment of state-owned enterprises (SOEs) and expand financing support and the direction of green transition for non-SOEs.

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