Green Credit Policy and Digital Transformation of Highly Polluting Enterprises--Quasi-natural experiments based on the Green Credit Guidelines

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Abstract. This study empirically analyzes the impact of green credit policy implementation on the digital transformation of highly polluting enterprises by constructing a double difference model using observed data of A-share listed companies in Shanghai and Shenzhen in China from 2007-2021, and using the Green Credit Guidelines promulgated in 2012 as a quasi-natural experiment. It is found that: (1) the implementation of green credit policy inhibits the digital transformation of highly polluting enterprises; (2) financing constraints are an important mechanism by which green credit policy inhibits the digital transformation of enterprises; and (3) the inhibitory effect of green credit policy on the digital transformation of enterprises is more significant for state-owned enterprises and relatively weak for large-scale enterprises. The research in this paper helps to systematically and comprehensively understand the impact of green credit on the digital transformation of enterprises, scientifically assess the policy effects of green credit policies in China, and is important for understanding how green financial policies in China affect the transformation and development of highly polluting enterprises, and provides reference for the future green financial policy formulation of government departments.

Keywords: Green Credit, highly polluting enterprises, Digital transformation.

1. Introduction

With the rapid advancement of the new round of technological revolution, digital intelligent technology is completely changing the traditional production model, and the digital economy is gradually replacing the traditional industrial economy as the core driving force of economic development in the new era. 2022 In July, the China Academy of Information and Communication released the China Digital Economy Development Report (2022). According to the report, the scale of China's digital economy reached RMB 45.5 trillion in 2021, with a year-on-year growth rate of 16.2%. The growth rate of the digital economy was 3.4 percentage points higher than the growth rate of GDP in the same period, and the contribution of the digital economy to the national economy continued to increase, reaching 39.8%. The scale of digitisation of industries grew by 17.2% to a whopping $36.2 trillion, accounting for 32.5% of GDP. Among them, chemical, iron and steel, non-ferrous metal smelting and other highly polluting traditional pillar enterprises, whose development is crucial to the lifeline of the national economy, but the crude development model has led to inefficient use of resources, overcapacity and lack of development momentum, and thus need to use digital transformation to get rid of the original traditional business management model, improve the efficiency of resource use through resource reallocation, overcome the existing difficulties and achieve sustainable development. However, according to the "2022 China Enterprise Digital Transformation Index Study", the threshold and risks of digital transformation are relatively high and uncertain, and highly polluting enterprises often face problems such as not knowing how to transform and not daring to transform. The road to digital transformation is still difficult. As digital transformation is an important strategic decision for enterprises, they need to make a wise choice. Therefore, it is important to study the issues related to digital transformation in order to provide enterprises with sound advice and guidance to facilitate the successful implementation of digital transformation.

The established literature has mainly studied digital transformation of enterprises in terms of the economic consequences of digital transformation on enterprises and the influencing factors of digital transformation. From the perspective of economic consequences, digital transformation can effectively improve technological innovation, enhance the level of factor allocation and risk control, and help to increase the value level of enterprises (Huang Dayu et al., 2021). The deepening degree of digital transformation triggers a change in the way enterprises are managed, driving a shift in corporate goals and innovation in governance structures (Qi and Xiao Xu, 2020) and disrupting the corporate value creation process (Nambisan et al., 2017; Frynas et al., 2018). In addition, corporate digital transformation significantly reduces corporate financing costs (Che Dexin et al., 2021), expands corporate exports (Yi Jingtao and Wang Yuehao, 2021), improves corporate governance (Qi Huaijin et al., 2020), reduces corporate audit costs (Zhang Yongshen et al., 2021), and empowers and facilitates corporate innovation (Fu Shuxian, 2022), which in turn improves corporate performance (Mikalef and Pateli, 2017; Bai Fuping et al. 2022; Yi Luxia et al. 2021), digital transformation has improved the business performance of enterprises. However, on the other hand, digital transformation is a systematic process, and in the practice of digital transformation, enterprises not only have to disrupt their traditional business models, but also have to continuously research and develop innovations, adjust their organisational structures, and restructure their resources, which is a time-consuming, costly and difficult process.Hajli and Sims (2015) found that digital transformation was effective only in some enterprises. Scholars also found that digitalisation was not integrated with the firm's original resources and that the dysfunctional management capabilities triggered by the new technology inhibited the positive impact of business model innovation (Qi, I.D. and Cai, Chengwei, 2020). Xu Mengzhou and Lü Tie (2022) found that the hidden costs of firms were raised due to the uncertainty of digital transformation, which was detrimental to the financial performance of firms. Based on the above analysis, it is clear that existing studies have different views on digital transformation, and therefore, it is important to explore digital transformation in depth.

Existing studies have analysed the factors influencing digital transformation of enterprises mainly from the market and government perspectives. Zhou Zhou and Wu Xintong (2022) found that IPR protection facilitates digital transformation of enterprises by promoting the "R&D effect", "talent effect" and The "market effect" facilitates digital transformation of enterprises. Shi Yupeng and Wang Yang (2022) found that improvements in the business environment reduced business costs while promoting innovation, which in turn facilitated digital transformation. Wu Fei et al. (2021) found that government spending on science and technology can stabilise the financial situation of enterprises, optimise their innovation behaviour, and help them undergo digital transformation. Cheng Qiongwen and Ding Hongyi (2022) argued that both add-on deductions for R&D expenses and tax breaks can facilitate digital transformation of enterprises. Existing studies mainly focus on the technological perspective and the market perspective to theoretically analyse the drivers, paths and economic consequences of digital transformation, while studies based on macro policies are relatively inadequate. In view of this, this paper attempts to explore the impact and mechanism of government policies on the digital transformation of enterprises and enrich the research in this area.

In February 2012, the China Banking Regulatory Commission (CBRC) issued the Green Credit Guidelines, the first document to regulate the management of green credit in China. According to the Guidelines, when allocating credit resources, financial institutions should conduct pre-credit reviews on environment, energy, and governance, as well as strengthen post-credit supervision, so as to help polluting enterprises implement energy conservation and emission reduction and promote sustainable and healthy economic development (Su Dongwei and Lian Lili, 2018). The Guidelines provide specific institutional arrangements for financial institutions to conduct green credit operations, which have a significant effect on limiting the innovation performance of polluting enterprises, as confirmed by an empirical study by Jinsong Zhang and Shanshan Lu (2022). Those highly polluting industries that were restricted exhibited more positive green innovation relative to those that were not restricted by green credit. (Wang Xin and Wang Ying, 2021). However, some scholars take the opposite view. Yu Bo (2021) found that after the Guidelines were introduced, the innovation output of highly polluting firms was significantly lower compared to other industries. According to the findings of Li Xinguang and Zhu Yanping (2021), there is a clear trend that the financing costs faced by highly polluting enterprises in terms of debt financing have been on the rise since the green credit policy was first implemented. This suggests that green credit policies have helped to increase the extent to which banks prioritise financing for environmentally friendly firms, and have also played a positive role in penalising polluting firms and reducing their financial leverage. Zhang Xiaoxiao and Hu Jinyan (2022) find that the implementation of green credit policies raises the level of financing constraints and financing costs for firms, reduces government subsidies, and thus discourages corporate investment spending. While enterprises are constantly innovating their own production and business models in digital transformation, digital transformation is not only a strategic decision for enterprises to follow the laws of economic development, but also an important strategic investment for enterprises in themselves. Therefore, this paper argues that the implementation of green credit policies is of great practical significance for highly polluting enterprises to achieve transformation and upgrade and lead sustainable development.

This paper examines the impact of green credit policies on the digital transformation of enterprises from the perspective of government macro policies. The research sample is selected from Shanghai and Shenzhen A-share listed companies from 2007-2021, and the Green Credit Guidelines promulgated in 2012 are used as a quasi-natural experiment to test the impact of green credit policies on the digital transformation of enterprises and its mechanism of action using the double difference method. The study finds that green credit policies can significantly inhibit the digital transformation of enterprises. The innovations and contributions of this paper are manifested in the following three aspects: (1) It enriches and expands the empirical research on the digital transformation of enterprises, and has guiding implications for enterprises' strategic decision-making. Digital transformation is a hot issue in academic circles, and the research results are abundant, but most of the existing studies focus on the economic consequences of digital transformation, with less coverage from the macro policy perspective, and few papers explore the impact of policies on enterprises' digital transformation from the national macro policy level. This paper fills a gap in the existing literature by exploring the impact of green credit policies on the digital transformation of enterprises from this novel perspective. (2) Most of the existing literature on digital transformation has focused on the manufacturing sector, with less attention paid to highly polluting enterprises. Compared with non-highly polluting enterprises, as highly polluting enterprises are more likely to cause environmental problems, which have significant externalities, such enterprises are therefore more likely to receive extensive attention from the state and all sectors of society, and when highly polluting enterprises cause environmental problems, the consequences they produce are often more serious and cause more adverse impacts, so the transformation of highly polluting enterprises is of important Therefore, the transformation of highly polluting enterprises is of great importance to the realisation of national green development goals. This paper takes highly polluting enterprises as the research object and verifies the binding effect of green credit policies on the digital transformation of highly polluting enterprises. (3) From the perspective of green credit policy, the series of institutional arrangements made in the Guidelines are designed to promote energy conservation and emission reduction among highly polluting enterprises and to promote sustainable economic development. However, the empirical results show that the green credit policy has strengthened the resource constraints on highly polluting enterprises, which is not conducive to their transformation and upgrading and has produced negative spillover effects. From this perspective, this paper provides an important supplement and elaboration on the economic consequences of the green credit policy.

2. Theoretical analysis and hypothesis formulation

At present, the overall digital transformation of enterprises is still at a relatively preliminary stage, and the survey data of the SME Digital Transformation Analysis Report (2020) shows that the proportion of enterprises exploring digital transformation in the initial state is as high as 89%, and the majority of enterprises are facing the problem of "not being able to transform". Secondly, the production equipment of traditional high-pollution enterprises is not based on digital technology deployment, and high-pollution enterprises fail to develop Internet technology and computerisation in time due to poor management system and low level of R&D. This has led to the three major problems of low networking rate of production equipment, low usage rate of industrial software and low level of equipment intelligence. These problems are particularly acute in small-scale enterprises with limited financial and human resources, making it difficult for highly polluting enterprises to make the "jump" from automation to digitalisation. In addition, the key hardware and software required for the digital transformation of Chinese enterprises, such as operating systems, industrial software and key equipment, are heavily dependent on imports and the cost of imports is high. A larger proportion of state-owned enterprises (SOEs) are highly polluting than their non-SOE counterparts, which makes digital transformation even more difficult for SOEs. By internalising the external costs of the environment, the green credit policy transforms the environmental costs originally borne by society into costs borne by the polluting enterprises, thereby dynamically adjusting the opportunity costs of environmental pollution and mitigating the negative impacts of environmental pollution caused by highly polluting enterprises. Specifically, the Green Credit Policy places clear restrictions and limitations on highly polluting enterprises that pose environmental and social risks. According to the Green Credit Guidelines, banking financial institutions should establish environmental and social risk assessment criteria, assess and classify customers in accordance with the criteria, and implement differentiated management. Banks should establish special credit guidelines for industries with significant environmental and social risks, and will not provide corresponding credit support to enterprises with environmental and social non-compliance. In addition, green credit policies stipulate that financial institutions, when allocating credit resources, will grant smaller, shorter-term and more costly external financing to enterprises with low levels of environmental risk management and poor environmental information disclosure, and that enterprises with poor environmental performance face higher environmental liabilities (Sharfman and Fernand 2008). Whereas high polluting enterprises have large emissions of their own and relatively low levels of environmental risk management, and some studies have found that the quality of environmental information disclosure of high polluting enterprises decreases after the implementation of the policy (Liu and Cheng, 2022), high polluting enterprises usually need to cope with stricter financing thresholds and higher financing costs, and the relevant provisions of the green credit policy increase the difficulty for high polluting enterprises to access credit resources and exacerbate the This paper argues that the implementation of the green credit policy has increased the difficulty of accessing credit resources for highly polluting enterprises and exacerbated the resource constraints on them. This paper argues that the implementation of green credit policies has a disincentive effect on the digital transformation of highly polluting enterprises.

In summary, the following research hypothesis H1 is proposed in this paper:

Hypothesis H1: The implementation of green credit policies inhibits the digital transformation of highly polluting enterprises.

3. Tudy design

3.1 Sample selection and data sources

In this study, the research sample was listed companies in Shanghai and Shenzhen A-shares from 2007 to 2021. After screening and data processing, a sample set containing 28,899 observations was finally obtained. During the sample screening process, the sample of companies in the financial sector, companies that were ST, ST and PT, and those with missing data for some variables were excluded. In order to eliminate the effect of extreme outliers, a tail-shrinking process of the upper and lower 1% quantile was performed in this paper. Observations on digital intangibles were obtained from firms' annual reports, and observations on corporate governance, firm characteristics, and financial data were obtained from the Cathay Capital (CSMAR) database.

3.2 Core variable definitions

3.2.1 Explanatory variables

The core explanatory variable in this paper is the digital transformation (DT) of enterprises. Referring to the studies on digital transformation by He Fan et al. (2019) and Zhang Lina et al. (2021), this paper uses word frequency statistics to measure the digital transformation of enterprises, i.e. the frequency of digital-related intangible assets in the intangible assets of enterprises is accumulated and the number of word frequencies counted is used as a reference indicator. For digital intangible assets, this paper uses the "digitalisation" in the "14th Five-Year Plan" and the "Notice of the State Council on the Issuance of the 14th Five-Year Plan for the Development of Digital Economy" and other relevant policy documents as a reference indicator. Based on the elaboration of "digitization", this paper extracts words and terms related to digitization and establishes a keyword database of digitization-related intangible assets. This process requires an in-depth study of the policy documents, mining them for definitions, key areas, application scenarios, infrastructure and other aspects of digitisation, and extracting the terminology and keywords therein to ensure that the keyword database is comprehensive and accurate. Based on the obtained thesaurus to create keywords for the search, the main keywords included software, management system, information system, cloud computing, cloud platform, digitalisation, etc. The data related to intangible asset items in the annual reports of A-share listed companies in Shanghai and Shenzhen from 2007-2021 were then downloaded from the Guotaian database, and the frequency of the above keywords appearing in the annual statements of enterprises was counted as an initial measure of the degree of digital transformation of that enterprise. In addition, due to the obvious right-skewed tendency in the statistical distribution of word frequencies, the accumulated statistical word frequencies are logarithmically processed in this paper.

3.2.2 Explanatory variables

The core explanatory variable in this paper is the cross product term (Treat×Post) of industries restricted by green credit policy (Treat) and green credit policy (Post). treat is a dummy variable reflecting whether an enterprise belongs to a highly polluting industry restricted by green credit policy after the release of the Green Credit Guidelines, and takes the value of 1 if the enterprise belongs to a highly polluting industry; otherwise, it takes the value of 0. green The identification of credit-restricted enterprises is borrowed from Wang Xin and Wang Ying (2021) by referring to the identification of green credit-restricted industries as proposed in the Key Evaluation Indicators for Green Credit Implementation (the Indicators), and the industries to which the Class A environmental and social risk enterprises belong as proposed in the Indicators are identified as green credit-restricted industries. Based on the implementation time of the Green Credit Policy Guidelines, this paper sets Post as a dummy variable for the time before and after the implementation of the policy, with a value of 1 for the year 2012 and later and 0 for the year before 2012.

3.2.3 Control variables

In this paper, we will refer to the studies of Cheng Qiongwen (2022) and Wang Hongming (2022) and select the basic characteristics indicators of listed companies and corporate governance-related factors as control variables, where each variable is calculated with the corresponding formula. In addition, this paper also controls for time and industry fixed effects. The specific variables are defined as shown in Table 1.

Table 1: Definition of variables

Variable type	Name	Symbol Definition Description	Symbol Definition Description
Explanatory variables	Digital transformation of enterprises	*DT*	Natural logarithm of the frequency of the word digital intangibles
Explanatory variables	Group dummy variable	*Treat*	Listed companies belonging to highly polluting industries restricted after the issuance of the Guidelines take a value of 1, otherwise 0
	Policy dummy variables	*Post*	2012 and onwards takes the value of 1, otherwise 0
	Double difference variables	*Treat×Post*	Group dummy variable x Policy dummy variable
control variable	Business Size	*SI*	Natural logarithm of total assets
	Return on Total Assets	*ROA*	Net profit / Total assets
	Cash-to-Asset Ratio	*Cashratio*	Cash and cash equivalents balance at end of period/total assets
	Capital Intensity	*SD*	Total Assets / Operating Income
	Age of the business	*Age*	The logarithm of the current year minus the year in which the enterprise was listed plus 1
	Nature of ownership	*SOE*	If the enterprise is a state-owned enterprise, the value is 1, otherwise it is 0
	Ratio of independent directors	*DL*	Number of independent directors/total number of directors
	Shareholding ratio of the first largest shareholder	*OW*	Ratio of the number of shares held by the largest shareholder to the total number of shares at the end of the year

3.3 Research model

Drawing on the empirical methods of Su, Dongwei et al. (2018) and Liu (2019), this paper constructs a double difference model using the Green Credit Guidelines issued in 2012 as a quasi-natural experiment to test:

$$DT = \alpha_0 + \alpha_1 Treat \times Post + \alpha_2 Treat + \alpha_3 Post + \lambda Controls + Ind + Year + \varepsilon \quad (1)$$

Treat is a dummy variable reflecting whether the enterprises belong to the highly polluting industries restricted by the green credit policy after the release of the Green Credit Guidelines. Post is a dummy variable for the time before and after the implementation of the policy. The coefficient of Treat×Post represents the impact of the implementation of the green credit policy on the digital transformation of enterprises. If α_1 is significantly smaller than 0, it indicates that the green credit policy inhibits the digital transformation of high polluting enterprises. controls are control variables. ind and yr are industry and time fixed effects respectively.

4. Empirical Results and Analysis

4.1 Descriptive statistics and correlation analysis

In this study, descriptive statistical analysis was conducted to provide insight into the digital transformation of companies and the state of distribution of other variables. In Table 2, the mean value of DT is 1.179, the minimum value is 0, the maximum value is 4.836 and the standard deviation is 0.32, indicating that there is a wide variation in the degree of digital transformation of companies, which vary in their efforts and progress in digital transformation. In addition, the values of the other variables are within a reasonable range and in line with the actual situation. In order to ensure the reliability of the subsequent analysis results, this paper also conducted correlation analysis on the control variables. The results show that there is no significant problem of multicollinearity between the variables, which provides a guarantee for the subsequent analysis.

Table 2: Descriptive statistics

Variable	Mean	Standard	deviation	Max
DT	1.179	0.321	0	4.836
Treat	0.212	0.409	0	1
Post	0.802	0.398	0	1
Treat×Post	0.170	0.375	0	1
SI	22.10	1.267	19.830	26.000
ROA	0.039	0.067	-0.291	0.211
Cashratio	0.174	0.137	0.011	0.676
SD	2.446	1.977	0.393	12.690
Age	2.859	0.359	1.675	3.516
SOE	0.364	0.481	0	1
DL	0.375	0.053	0.308	0.571
OW	34.640	14.800	8.780	73.980

4.2 Basic regression results

Table 3 presents the results of the empirical model regressions on green credit and digital transformation of high polluting enterprises. The regression results in column (1) are the regression results of the model without considering the province fixed effect; while considering the possible regional differences in policy implementation, this paper adds the province fixed effect to the regression model in column (2). After the introduction of the interaction term Treat×Post, the regression coefficients of the two models are -0.017 and -0.045 respectively, and the significance level of these coefficients are both 5%. These results suggest that the implementation of green credit policies inhibited the digital transformation of highly polluting firms to some extent, and H1 was verified.

Table 3: Multiple linear regression results

Variables	(1)	(2)
	DT	*DT*
Treat	-0.100***	-0.009
	(-7.250)	(-0.379)
Post	-0.020	0.023
	(0.815)	(0.509)
Treat×Post	-0.017**	-0.045**
	(-2.020)	(-2.500)
SI	-0.002	0.008
	(-0.564)	(1.361)
ROA	-0.083***	-0.054
	(-2.649)	(-1.093)
Cashratio	0.043**	-0.025
	(2.404)	(-0.806)
SD	0.002	-0.006**
	(1.129)	(-2.308)
Age	0.068***	0.023
	(2.580)	(0.474)
SOE	0.015	-0.037*
	(1.251)	(-1.920)
DL	-0.055	-0.137*
	(-1.168)	(-1.839)
OW	-0.001***	-0.002***
	(-5.009)	(-3.644)
Constant	1.018***	1.157***
	(10.168)	(6.070)
N	28,899	28,899
Adj. R-sq	0.050	0.053
Year	Yes	Yes
Industry	Yes	Yes
Province	No	Yes

Note: Robust standard errors for clustering at the province level are reported in brackets, with ***, ** and * indicating significant at the 1%, 5% and 10% levels respectively. Same for the following tables.

4.3 Robustness tests

4.3.1 Parallel trend test

In order to test the reliability of the double difference model, the group dummy variable (Treat) is cross-multiplied with the time dummy variable from 2007-2015 respectively, using the period before the implementation of the policy as the base year, to construct a period dummy variable for each year within the sample years, which is substituted into the base model for regression analysis.

Figure 1 illustrates the results of the parallel trend test. The results show that none of the estimated coefficients of the interaction terms for 2007-2010 are significant, indicating that the trend of the data in the control and experimental groups remained largely consistent before the introduction of the green credit policy, with no significant differences in change, confirming the reliability of the double-difference model in this paper. In addition, the estimated coefficients of the interaction terms are significantly negative in 2012 and later years, indicating that the green credit policy did inhibit the digital transformation of highly polluting enterprises.

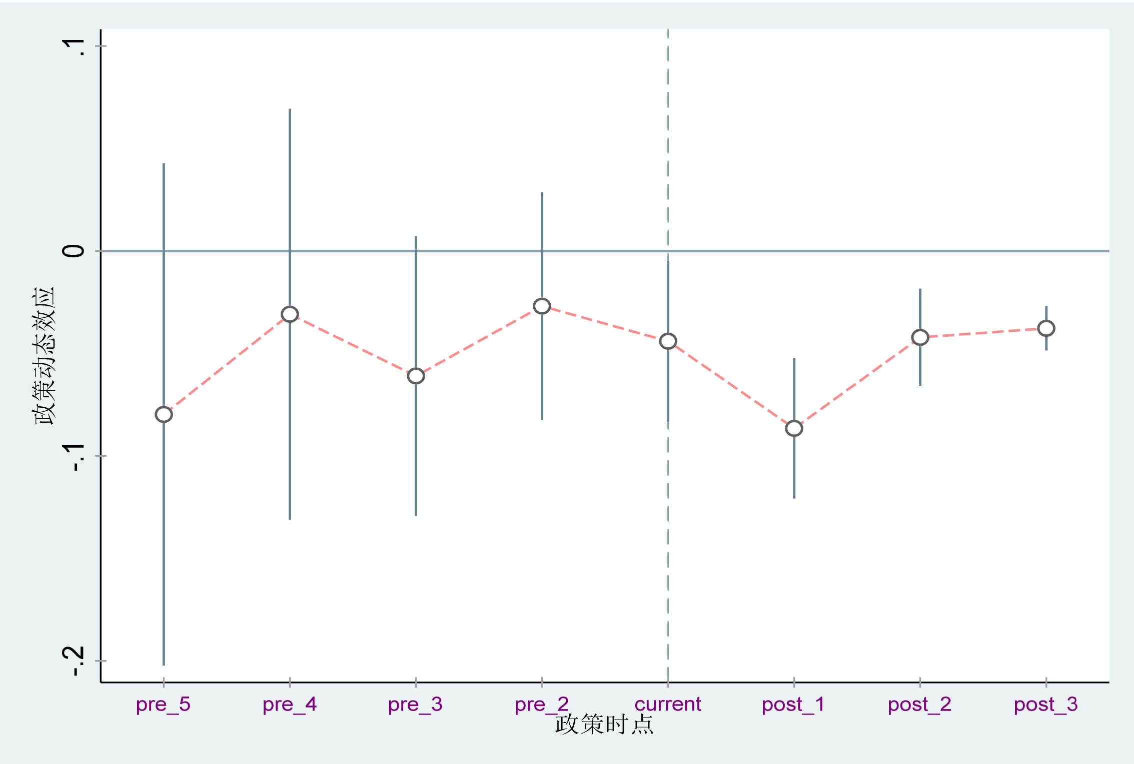

Figure 1. Parallel trend test for the double difference model

4.3.2 Placebo test

This paper confirms the results of the impact of green credit policies on the degree of digital transformation of high polluting firms, drawing on the randomised experiments in Li et al. (2016) and La Ferrara et al. (2012). Specifically, the paper constructs randomised experiments at both the implementation time and firm levels by randomly 'screening' firms and randomly generating policy implementation times. The results of these randomised experiments were regressed to obtain a distribution of the estimated coefficients of the Treat×Year coefficients to verify the relationship between green credit policies and changes in other factors.

The distribution diagram in Figure 2 shows that the estimated coefficients of the Treat×Year coefficients are concentrated around 0, indicating that no significant influences were missed in the model setting and the core conclusion is further verified that green credit policies do have a negative effect on the digital transformation of highly polluting enterprises. In addition, the above steps were repeated 500 times in this paper in order to further enhance the validity of the placebo test, which allowed for more reliable conclusions. These results indicate that the conclusions obtained in this paper are robust and provide a basis for subsequent research.

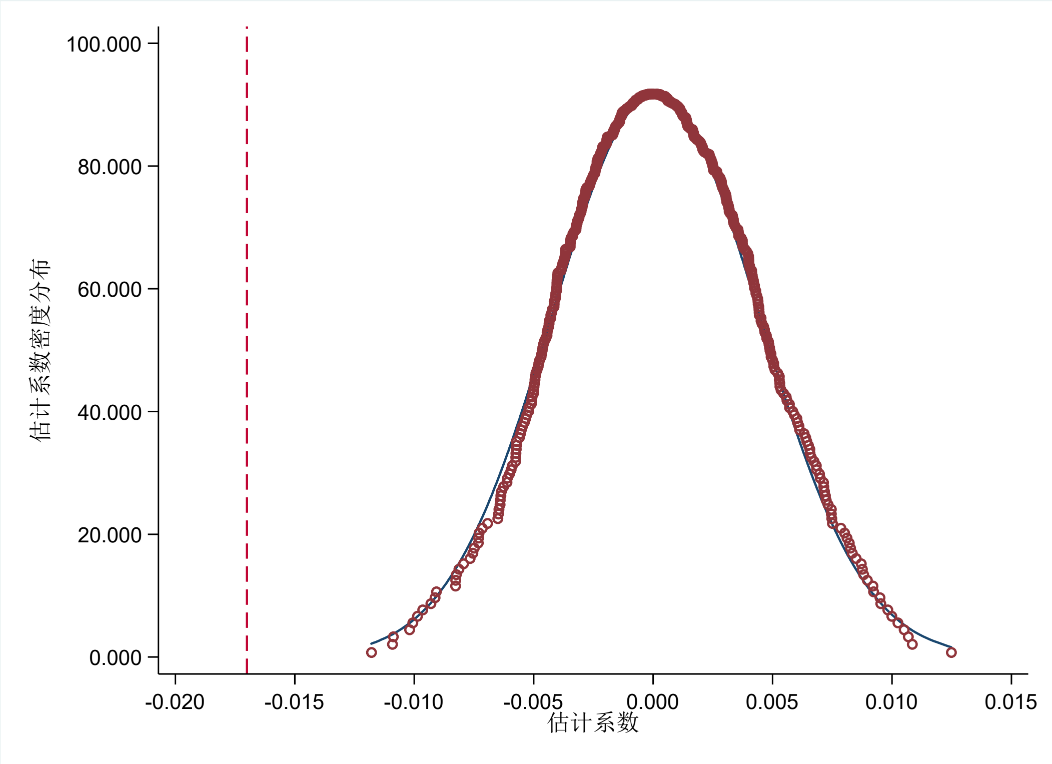

Figure 2. Placebo test

4.3.3 PSM+DID

Considering the possible endogeneity problem of sample selectivity of the policy and in order to more accurately select a reliable control group, this paper uses propensity score matching analysis to test the causal relationship between the implementation of green credit policies and the digital transformation of enterprises, all other things being equal.

In this paper, a logit model is developed and a nearest neighbour 1:1 matching is adopted for the control group sample, with control variables that remain consistent with the baseline model when matched. Table 4, column (1) shows the regression results for the matched samples, with the interaction term coefficient significantly negative, which is consistent with the empirical findings above, which fully demonstrates the robustness of the baseline regression results.

4.3.4 Substitution of indicators for explanatory variables

To further test the robustness of the results, this paper uses the ratio of digital intangible assets to total intangible assets as a proxy for the digital transformation of enterprises. Column (2) of Table 4 presents the regression results after replacing the variables, and the coefficient of the interaction term is still significantly negative, in line with the previous findings.

4.3.5 Adding control variables

Considering the omitted variable issue, this paper adds government subsidies (SU), firm growth opportunities (MA) and whether the auditor is from the Big 4 (Big4) as control variables in the baseline model. The results of the test in column (3) of Table 4 show the regression results after the additional variables, with the coefficient of the interaction term being significantly negative, in line with the previous findings.

Table 4: Robustness tests

Variables	(1)	(2)	(3)
	PSM	Variable substitution	Additional variables
Treat	-0.013	-0.035*	-0.092***
	(-0.554)	(-1.738)	(-6.635)
Post	0.024	0.106***	0.028
	(0.530)	(2.937)	(1.129)
Treat×Post	-0.046**	-0.084***	-0.017*
	(-2.557)	(-6.113)	(-1.958)
SU			0.004**
			(2.314)
MA			0.001
			(1.321)
Big4			0.011
			(0.715)
Constant	1.061***	0.862***	1.042***
	(6.230)	(5.960)	(10.308)
N	10,134	28,664	28,585
Control Variable	Yes	Yes	Yes
Adj. R-sq	0.041	0.028	0.050
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes

4.3.6 Controlling time trends

Considering that the effect of green credit policy implementation and the degree of digital transformation of enterprises have a time trend, this paper adds a regression analysis that includes a time trend term for enterprises to the baseline regression results. To avoid the problem of long sample selection time, this paper only considers the sample of enterprises in the three years before and after the implementation of the green credit policy, i.e. the sample data is controlled in the time window of 2009-2015. The test results show that the estimated coefficients of the interaction term for 2009-2011 are not significant, while the estimated coefficients of the interaction term for 2012 are significant at the 1% level of significance, eliminating the effect of time trends and further enhancing the reliability of the main findings of this paper. Regression results are not shown for space limitations.

5. Further analysis

5.1 The mediating effect of financing constraints

The previous study has confirmed that the implementation of green credit policies inhibits the digital transformation of firms, but it is only a holistic portrayal of the relationship between green credit policies and the digital transformation of firms, and has not yet examined the possible pathways of influence. In this paper, we refer to the study by Wen Zhonglin and Ye Baojuan (2014) to identify and test the mechanism paths that target the impact between green credit policies and the digital transformation of enterprises.

The Green Credit Guidelines require financial institutions to allocate credit resources by raising the lending threshold in terms of environmental protection pollution control and energy conservation, restricting loans to highly polluting enterprises, and increasing their financing costs while reducing loan maturity. This paper argues that the introduction of green credit policies has raised the financing constraints of highly polluting enterprises, making them unable to provide sufficient financial support for digital transformation activities, which in turn inhibits their digital transformation. Therefore, to investigate the possible mediating role of financing constraints, this paper constructs the following model based on model (1):

$$SA = \beta_0 + \beta_1 Treat \times Post + \beta_2 Treat + \beta_3 Post + \lambda Controls + Ind + Year + \varepsilon \quad (2)$$

$$DT = \gamma_0 + \gamma_1 Treat \times Post + \gamma_2 SA + \gamma_3 Treat + \gamma_4 Post + \lambda Controls + Ind + Year + \varepsilon \quad (3)$$

In order to assess the financing constraints faced by firms, this paper adopts the SA index as a measure, which is based on the financing constraint measure of Ju et al. (2013) and aims to reflect the degree of financing constraints faced by firms. Specifically, a negative SA index with a larger absolute value indicates a greater financing constraint faced by the firm. The results of the tests of the financing constraint mechanism are presented in the table. The results in (1) indicate that in the main model without the inclusion of the financing constraint control variables, green credit policies still significantly inhibit firms' digital transformation, implying that green credit policies have some inhibitory effect on firms' digital transformation. However, the results in column (2) show that the regression coefficient between Treat×Post and SA is significantly negative after the inclusion of the control variable for financing constraints, suggesting that the implementation of green credit policies has strengthened the degree of financing constraints faced by high polluting firms. Meanwhile, the results in column (3) show that the coefficient of SA is significantly positive after alleviating firms' financing constraints, suggesting that alleviating firms' financing constraints helps facilitate their digital transformation. However, the coefficient of Treat×Post remains significantly negative, suggesting that financing constraints play a partially mediating role in the inhibition of firms' digital transformation by green credit policies. Thus, the implementation of green credit policies strengthens the financing constraints of highly polluting firms, which in turn inhibits their digital transformation.

Table 5: Intermediary effects test

Variables	（1）	（2）	（3）
	DT	*SA*	*DT*
SA			0.121***
			(3.836)
Treat×Post	-0.017**	-0.004*	-0.015*
	(-2.020)	(1.920)	(-1.648)
Treat	-0.100***	-0.001	-0.100***
	(-7.250)	(-0.494)	(-7.238)
Post	-0.020	0.070***	0.010
	(0.815)	(13.081)	(0.411)
Constant	1.018***	-2.740***	1.412***
	(10.168)	(-127.348)	(10.968)
N	Yes	Yes	(10.968)
Control Variable	28,899	28,899	28,899
Adj. R-sq	0.050	0.102	0.051
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes

5.2 The regulatory role of the nature of property rights

A study points out that there are differences in the policy effects generated by environmental regulation policies for enterprises with different ownership during China's economic transition (Jin, 2020). In the traditional heavy industry sector China has a large share of state-owned enterprises, with high pollution and high emission enterprises occupying a large proportion of the state-owned asset structure. According to the National Bureau of Statistics, state-owned enterprises account for a large proportion of the oil and gas extraction industry, the coal mining industry and the electricity and heat production and supply industry, at 94.7%, 76% and 87.3% respectively. As there are more energy-consuming and high-emission enterprises among state-owned enterprises, green credit policies may place more emphasis on restrictions and limitations on such enterprises, which in turn may affect their digital transformation. Therefore, this paper argues that the nature of enterprise ownership may have a moderating effect on the impact between green credit policies and the digital transformation of enterprises.

The table shows the moderating effect test, and the regression results indicate that the inhibitory effect of green credit policies on firms' digital transformation is stronger among state-owned enterprises. Specifically, the regression coefficients in columns (1) and (2) show that the regression coefficient of Treat×Post is significantly negative for the SOE group, indicating that green credit policies have a more significant inhibitory effect on the digital transformation of SOEs. However, for the non-SOE group, the regression coefficient of Treat×Post is not significant, indicating that the impact of green credit policies on the digital transformation of non-SOEs is not significant. This finding indicates a difference in the effect of green credit policies on digital transformation between SOEs and non-SOEs, with green credit policies having a stronger inhibitory effect on digital transformation for SOEs.

5.3 The moderating role of firm size

To further examine the possible differences in the policy effects of green credit policies on enterprises of different sizes, this paper further examines the moderating effect of enterprise size. Compared to small-scale enterprises, large-scale enterprises have more robust internal control and management systems, as well as stronger research and development capabilities and production technologies, and are better able to cope with the environmental regulatory pressure brought about by the policy. Secondly, large-scale enterprises are often the backbone of the local economy and are often given more policy support by the government. Moreover, due to the brand effect, it is easier for large-scale enterprises to obtain financing or loans due to their high reputation in order to reduce the financial pressure brought by the policy. Therefore, the impact of firm size on the relationship between green credit policies and the digital transformation of firms may have a moderating effect. In this paper, the natural logarithm of a firm's total assets is used to measure firm size. The regression results in columns (3) and (4) of the table show that the regression coefficient of Treat×Post remains significantly negative for small-scale firms, while the regression coefficient of Treat×Post becomes insignificant for the large-scale firm group. This indicates that the smaller the size of the firm, the stronger the inhibitory effect of green credit policy on the digital transformation of the firm. It can be seen that the inhibitory effect of green credit policy on the digital transformation of high polluting enterprises is affected by the size of the enterprises, and the inhibitory effect of green credit policy on the digital transformation of small-scale enterprises is stronger.

Table 6: Tests for moderating effects

Variables	（1）	（2）	（3）	（4）
	State-owned enterprises	Non-state-owned enterprises	Large-scale enterprises	Small-scale enterprises
	DT	*DT*	*DT*	*DT*
Treat×Post	-0.033***	-0.026	-0.035	-0.040***
	(-2.870)	(-3.879)	(-6.455)	(-5.079)
Constant	2.179***	1.183***	1.227***	1.598***
	(11.33)	(12.08)		
	(10.742)	(11.431)	(4.862)	(11.845)
N	10527	18372	14422	14477
Control Variable	Yes	Yes	Yes	Yes
Adj. R-sq	0.049	0.052	0.036	0.063
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes

6. Conclusions and insights

Using observed data of A-share listed companies in Shanghai and Shenzhen in China from 2007 to 2021, this study uses the Green Credit Guidelines promulgated in 2012 as a quasi-natural experiment and applies the double difference method to verify the impact effects and conditional mechanisms of green credit policy implementation on the digital transformation of highly polluting enterprises. The findings show that: (1) the implementation of green credit policy inhibits the digital transformation of highly polluting enterprises, and a series of robustness tests indicate that the findings are robust and reliable; (2) green credit policy indirectly inhibits the digital transformation of highly polluting enterprises by strengthening the financing constraints of highly polluting enterprises; (3) the inhibitory effect of green credit policy on digital transformation is more significant for state-owned enterprises and small-scale enterprises. The research in this paper contributes to a systematic and comprehensive understanding of the impact of green credit on the digital transformation of enterprises, a scientific assessment of the policy effects of China's green credit policy, and is important for understanding how China's green financial policy affects the transformation and development of highly polluting enterprises, and provides a reference for the future development of green financial policies by government departments.

The policy implications of this paper's research are as follows: (1) After the implementation of the green credit policy, financial institutions strictly limit the credit support given to highly polluting enterprises, raising the financing threshold for highly polluting enterprises and optimising the allocation of resources, with obvious policy effects, but the implementation effects of the policy are likely to vary depending on the nature of the enterprises' property rights and the scale of the enterprises. In order to weaken or eliminate the asymmetry of the policy effect, while continuing to promote the green credit policy, the state should build a differentiated credit assessment system, create a good financial ecological environment and guide highly polluting enterprises to achieve a green transformation of their industrial structure. (2) While the government should exercise strict control, it should also provide precise support. In the short term, green credit's lending restrictions on highly polluting enterprises will help them eliminate backward production capacity, but excessive restrictions will lead to restricted financing for highly polluting enterprises in the exploration and development stage of digital transformation, insufficient development momentum and difficulties in digital transformation, deviating from the long-term objectives of green credit policies. To this end, the government should set differentiated criteria to help and encourage enterprises with development potential, eliminate enterprises with backward production capacity, dynamically adjust the intensity of restrictions on highly polluting enterprises, guide and support highly polluting enterprises to raise their environmental awareness and actively undertake digital investment and transformation, and help highly polluting enterprises to smoothly go through the transition period from traditional production mode to digital production, so as to better promote the green credit policy implementation. (3) Enterprises should actively engage in digital transformation. In the context of the current "double carbon target", the State has introduced a green credit policy. In order to achieve the national goal of green and sustainable development, the State may impose stricter restrictions on backward and highly polluting industries in the future, and highly polluting enterprises should raise their awareness of environmental protection, adapt more proactively to the needs of China's new development stage and change their the original traditional crude production model, strengthen technological research and development, promote green innovation, eliminate backward production capacity, improve the competitiveness of enterprises and gradually achieve digital transformation.

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