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Green Credit Policy and Corporate Productivity: Evidence from a Quasi-natural Experiment in China

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A B S T R A C T

Taking the implementation of the "Green Credit Guidelines" in China in 2012 as an exogenous shock, we adopt the difference-in-differences (DIDs) method to explore the influence of the green credit policy on total factor productivity (TFP). We show evidence of a significant and positive correlation between green credit and corporate total factor productivity, and this result is robust to a series of robustness tests. In addition, the improvement is particularly evident for non-SOEs, small-scale firms, firms with weak external supervision, and firms in developed areas of eastern China. Moreover, the green credit policy mainly affects corporate total factor productivity through promoting technological innovation and enhancing resource allocation efficiency. Overall, green credit promotes the win-win development of the environment and the economy.

1. Introduction

To achieve rapid economic development, many countries, led by the United States and Japan, have chosen the path of "pollution first, treatment later." This development path has caused problems such as a shortage of resources, aggravation of the greenhouse effect, and serious pollution (Hao et al., 2007; Ramalingam et al., 2018). In recent years, governments of various countries have set environmental protection targets and improved their environmental regulations, expecting to achieve efficient utilization of resources, neutral carbon targets, and environmental improvement by optimizing the industrial structure, promoting firm transformation, and finally achieving sustainable economic development (Horbach, 2008; Hojnik and Ruzzier, 2016; Cui and Jiang, 2019). As a concrete form of environmental regulation in the financial market, green credit is a kind of financial innovation to manage environmental issues effectively (La Porta et al., 2002). Specifically, the term green credit policy refers to financial institutions, such as banks, supplying environment-friendly firms with preferential interest rates while raising interest rates for or restricting loans to heavily polluting firms when issuing loans to achieve sustainable development through the rational allocation of credit funds (Nandy and Lodh, 2012; He et al., 2019).

Previous literature has found that green credit helps banks to adjust their credit structure by increasing the loan support for green projects, reducing loans for high-pollution projects, and further reducing the non-performing loan ratio (Cui et al., 2018). Meanwhile, green credit is associated with corporate financing capacity, the investment level, technological innovation, and firm performance (Su and Lian, 2018; Ling et al., 2020). Making full use of external resources such as credit and improving production efficiency are the key for firms to achieve growth and development and maintain a competitive advantage. However, the green credit policy imposes new constraints on corporate loans, and whether it will further affect the growth efficiency of firms has not been fully explored. Thus, this paper aims to investigate the influence of the green credit policy on corporate total factor productivity.[1]

Based on the prior literature, we infer that environmental regulation

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[1] The American economist Solow pointed out that total factor productivity is the "surplus" that cannot be explained by the input growth of labor, capital, and other factors. It can reflect the efficiency of transforming input into output and is an important proxy for corporate economic growth efficiency.

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could have two potential impacts on corporate total factor productivity (hereafter TFP). First, the compliance cost[2] theory argues that environmental regulation is equal to imposing additional constraints on the corporate decision-making process (Palmer et al., 1995) and increasing the difficulty and cost of production, sales, and management. Under these circumstances, the increased production cost may reduce firms' investment in production capacity improvement, thus reducing their total factor productivity (Becker, 2011; Hering and Poncet, 2014). In contrast, the "Porter hypothesis" holds that, although environmental regulation increases the corporate production cost in the short term, appropriate environmental regulation is beneficial, stimulating R&D investment and corporate innovation. The resulting improvement of the technological production process can compensate for the environmental regulation cost (Porter and Linde, 1995; Greenstone and List, 2012) and further enhance corporate total factor productivity.

According to the above two theories, as a concrete form of environmental regulation, green credit may reduce or enhance corporate total factor productivity. Therefore, whether and how a green credit policy affects corporate total factor productivity is still an important empirical question. By examining the influence of the green credit policy in the Chinese market on corporate total factor productivity, this paper aims to explore whether the green credit policy is conductive to promoting the harmonious development of the economy and the environment and to clarify further the relationship between environmental regulation and growth efficiency.

We use the Chinese market to explore this relationship for three main reasons. First, the "Green Credit Guidelines" (hereafter Guidelines) implemented in 2012 provide a good quasi-natural experiment for our research. They made relatively specific arrangements for financial institutions regarding credit. Specifically, (i) banks are required to distinguish the support direction and key areas, formulate special credit guidelines for industries with major environmental risk, and implement differentiated and dynamic credit policies; (ii) banking financial institutions should strengthen the management of credit approval and should not grant credit to customers whose environment and social performance are not up to standard; and (iii) environmental and social risk assessment checkpoints should be set up in the design, preparation, construction, and other links of a project that has been granted credit and the allocation of credit funds may be suspended or even terminated if there are major potential risks. China has established a green credit system framework with the Guidelines as the core. Therefore, the implementation of the Guidelines, as an exogenous shock, can effectively avoid the potential endogeneity problems (Cai et al., 2016) and sample selection bias (Greenstone et al., 2012) caused by indicators such as pollutant emissions and environmental expenditure to measure environmental regulation.

Second, the Chinese environment is conductive to studying the external governance role of financial institutions. Compared with developed markets, the regulatory institutions in the Chinese market are not perfect and the influence of institutional investors on firms is limited; thus, they cannot play a good role in external monitoring (Jiang and Kim, 2015). In addition, China's external audit, investor protection, and manager market are considered to be inefficient (Li et al., 2012). In the context of indirect financing, which is the dominant method in China, the credit policy becomes an important potential way to improve corporate governance (Gul and Goodwin, 2010; Dang et al., 2018). As a policy with clear guidance, the green credit policy facilitates people's understanding of the external governance role of financial institutions, such as banks.

Third, compared with developed markets, Chinese firms present a unique ownership structure (Yuan et al., 2016). The differences between SOEs and non-SOEs in political relations, financing capacity, and other aspects provide an ideal platform for us to investigate the heterogeneous effects of green credit on economic growth efficiency.

Taking the implementation of the Guidelines in 2012 as an exogenous shock, we use data on Chinese A-share public firms to study the impact of the green credit policy on TFP. The result shows that green credit is significantly positively associated with the TFP of heavily polluting firms, and this result remains robust after conducting a series of robustness tests, including an effectiveness test of the green credit policy, parallel trend test, placebo test, PSM-DID test, excluding the impact of other contemporary policies, replacing indicators, controlling for the impact of macroeconomic factors, and controlling for multiple fixed effects. Furthermore, the effect of the green credit policy on TFP is heterogeneous, and it is more obvious for non-SOEs, small-scale firms, firms with weak external supervision, and firms in developed areas of eastern China. The results also show that technological innovation and improved resource allocation efficiency are the potential channels through which the green credit policy affects the TFP of heavily polluting firms.

Our paper makes the following contributions. First, our research expands the relevant literature on green credit. The proposal of the "Equator Principle"[3] in 2002 triggered an extensive discussion in academia on green credit (Konishi and Tarui, 2015; Acemoglu et al., 2016; Su and Lian, 2018; Hu et al., 2020). However, regarding the micro impact of green credit, many scholars have limited their work to verifying the "Porter hypothesis" and exploring the impact of green credit on corporate innovation (Acemoglu et al., 2016; Aghion et al., 2016) and have rarely analyzed the relationship between green credit and economic growth efficiency further. Different from previous studies, this paper first explores the effectiveness of the green credit policy in China in 2012, providing relevant empirical evidence for the current disputes in green credit policy research (Su and Lian, 2018; Hu et al., 2020; Fan et al., 2021). By exploring the impact of green credit on the total factor productivity of heavily polluting firms, we find that the implementation of China's green credit policy plays a positive role. It enhances the supervision role of banks, improves firms' business decision making, promotes the improvement of corporate total factor productivity, and realizes the win-win situation of economic growth and environmentally sustainable development. Supporting Porter's hypothesis, this study supplements the literature related to green credit, which facilitates the further implementation of green finance policies, provides a certain reference for the environmental policies of other emerging markets, and promotes environmental protection.

Second, by exploring the economic mechanisms through which the green credit policy affects total factor productivity, we reveal the role of environmental regulation in firms' decision making and corporate governance and widely supplement the relevant literature (Chen et al., 2011; Jiang et al., 2015; Yuan et al., 2016; Zhong et al., 2016). We find that the green credit policy can promote the improvement of total factor productivity by improving technological innovation and resource allocation efficiency, providing a reference path for further improving social production efficiency. At the same time, the result provides a new explanation for the internal mechanism of the government and policies affecting firm production and operation activities.

Third, this paper enriches the research framework on the impact of environmental regulation, especially the green credit policy, on corporate total factor productivity. Regarding the impact of environmental

[2] Compliance cost: additional costs incurred by the regulated party to comply with the relevant regulations.

[3] The Equator Principle refers to the guidelines for project financing of environmental and social risks, which were formulated at the conference of international well-known commercial banks held in London by ABN AMRO, Barclays Bank, West Deutsche Bank, Citibank, and the International Finance Corporation under the World Bank in October 2002. The guidelines require financial institutions to make a comprehensive assessment of the potential environmental and social risks of a project when investing in it and to use financial leverage to promote a positive role for the project in terms of environmental protection and the harmonious development of the surrounding society.

regulation, most of the existing studies have been based on macro-level data but have paid less attention to firm characteristics (Li and Wu, 2017; Shen et al., 2019). After considering the heterogeneity of firm characteristics (firm ownership and firm size), this paper further explores the heterogeneity of the role of the external supervision mechanism. In addition, based on the unbalanced economic development and unreasonable resource allocation between regions, we investigate the differences in the effect of the green credit policy on total factor productivity from the perspective of regional heterogeneity, which makes the research more comprehensive and is of great significance in helping the government to formulate differentiated environmental regulation policies according to local conditions.

Fourth, our research has valuable policy implications. It finds that, since the implementation of the Guidelines in 2012, the bank loan scale of heavily polluting firms has been significantly constrained and their total factor productivity has been significantly improved. However, in non-heavily polluting firms, the green credit policy has had limited effects on the bank loan scale and TFP. At present, China's environmental policies still focus on the punishment effect, concentrating on the control of heavily polluting firms, while the degree of encouragement for green firms is insufficient. To realize the sustainable and healthy development of the economy and society further, the government should integrate the concept of green credit into all aspects and links of banking work and encourage banks to broaden the sources of green credit funds, innovate green products and services, support the development of green firms, and encourage the transformation and upgrading of heavily polluting firms.

The structure of this paper is as follows. Section 2 presents the institutional background and hypothesis development. Section 3 introduces the data and method. Section 4 and Section 5 present the empirical results and robustness results, respectively. Section 6 further analyzes the heterogeneous influence, and Section 7 examines the mechanisms through which the green credit policy affects corporate total factor productivity. The conclusion is provided in Section 8. To present the research content of this paper clearly, we draw a research framework.

2. Institutional background and hypothesis development

2.1. Institutional background

Green credit refers to a series of policies, institutional arrangements, and practices that use credit means to promote energy conservation and emission reduction and is specifically reflected in the "differential credit" policies of banking financial institutions. In 1974, the Federal Republic of Germany established the world's first policy-based environmental protection bank, named "Ecological Bank," which is responsible for providing preferential loans for environmental projects that general banks are unwilling to offer. In 1980, the United States promulgated the "Comprehensive Environmental Response," which clearly stipulates that commercial banks should be responsible for the environmental pollution of the projects for which they issue credit funds. Green credit policies have become a trend in the international arena and have received increasing support and attention from financial institutions. The most influential one is the famous "Equator Principle."

Compared with developed economies and emerging markets, such as those in the European Union,[4] China's green credit policy was created under certain environmental pressures and government promotion. Since the reform and opening up, China's economy has developed rapidly, but the ecological environment has also been damaged to a certain extent. China's policy of introducing "differential credit" into environmental protection can be traced back to the "Notice on Issues Related to Implementing Credit Policies and Strengthening Environmental Protection," issued by the People's Bank of China in 1995, requiring financial institutions to pay attention to natural resources and environmental protection and support the protection of ecological resources and the prevention and control of pollution among the factors considered by bank loans to promote the coordinated development of economic construction and environmental protection.

Since then, to curb the blind expansion of high-energy-consuming and high-polluting industries,[5] and to help and encourage firms to reduce their energy consumption and save capital, the former State Environmental Protection Administration, the People's Bank of China, and the China Banking Regulatory Commission jointly issued the "Opinions on Implementing Environmental Protection Policies and Regulations to Prevent Credit Risks" (hereafter Opinions) on July 12, 2007, requiring financial institutions to strengthen the coordination and cooperation of environmental protection and credit management, strictly implement environmental protection credit, and effectively prevent related risks. The Opinions used green credit as an important market tool for environmental protection, energy conservation, and emission reduction for the first time, marking the official launch of the green credit policy (Su and Lian, 2018). However, the document did not formulate specific implementation measures for the green credit policy. The vague policy rules made it difficult for banking financial institutions to grasp the points, and the Opinions did not achieve the expected effect of the policy.[6] Because the policy does not impose mandatory restrictions on banks, some banks still choose to continue to provide loans to heavily polluting firms for their own profitability purposes (Fan et al., 2021). In addition, because it was the initial implementation of the policy, banking financial institutions lack experience, and various problems have arisen, such as a lack of personnel with professional knowledge, supporting institutions, and systems within the banks, resulting in inefficient implementation of the Opinions (Zhang, 2021).

With the deepening of the understanding of the relationship between environmental protection and economic development, the green credit policy has been continuously deepened and enriched. In 2012, the China Banking Regulatory Commission issued the "Green Credit Guidelines," which became the programmatic document of China's green credit system. Unlike the Opinions in 2007, the Guidelines make relatively specific arrangements for financial institutions in terms of green credit work. The Guidelines point out that banking financial institutions should (i) promote green credit from a strategic perspective, effectively identify, measure, monitor, and control environmental and social risks in credit business activities and establish and continuously improve environmental and social risk management policies, systems, and procedures; and (ii) clarify the support direction and key areas of green credit, determine reasonable credit authorization and approval procedures, and deny credit to customers who do not comply with environmental and social performance requirements. Further, the Guidelines clarify the internal management and information disclosure

[4] Green finance in developed economies such as the Netherlands, Germany, the United States, France, and Japan started earlier, and its emergence was mainly the result of social responsibility movements and market mechanisms. In contrast, in the process of developing green finance in the European Union and other emerging economies, governments' support and guidance are more proactive. Through the use of tax incentives and government guarantees, governments encourage green environmental protection projects and actively drive private capital into the green finance economy through policy financial institutions.

[5] According to statistics, the industrial added value in the first half of 2007 increased by 18.5%, and the added value of the six energy-intensive industries, specifically petrochemicals, chemicals, building materials, steel, nonferrous metals, and electric power, increased by 20.1%, 1.6 percentage points higher than the industrial value.

[6] According to statistics from the China Banking Regulatory Commission, as of the end of May 2009, the balance of medium- and long-term loans of major financial institutions in "high pollution and high energy consumption" industries reached 2.3 trillion yuan, an increase of 23.43% over the same period in 2008.

requirements of banking financial institutions regarding the implementation of green credit. Regulators should promptly guide banking financial institutions to strengthen risk management and adjust credit investment. The promulgation and implementation of the Guidelines impose hard constraints on the environmental orientation of banks' and other financial institutions' credit lending, which have transformed China's green credit policy from an initially voluntary environmental policy into a mandatory environmental policy (Fan et al., 2021). In accordance with the Guidelines, the Tianjin Banking Regulatory Bureau imposed administrative penalties on Ping An Bank Co., Ltd. for providing financing to firms that did not meet environmental protection standards, which not only shows the determination of the banking supervision department to implement the green credit policy but also indicates that the Guidelines are mandatory to a certain extent.

Since then, under the guidance of the Green Credit Guidelines, China's green credit has developed rapidly. According to data disclosed by the China Banking and Insurance Regulatory Commission, the green credit balance of 21 major banks increased from RMB 4.85 trillion at the end of June 2013 to RMB 10.6 trillion at the end of June 2019, and the compound annual growth rate of China's green credit scale reached 13.90%. Therefore, most of the existing studies on the green credit policy have used the 2012 Green Credit Guidelines as their main research object (Ling et al., 2020).

2.2. Hypothesis development

There are controversies in academic circles about the impact of green credit on corporate total factor productivity. The compliance cost theory suggests that equipment procurement, R&D, and process upgrades require a large amount of capital costs, but the green credit policy has increased the financing constraints of heavily polluting firms, forcing firms to bear higher risks and sunk costs than they would face in a better financing environment (He et al., 2019; Zhang et al., 2020a,b). As a result, firms may reduce their capital investment in R&D, production, and investment activities, thereby losing their market share and competitive advantage and damaging their profitability and productivity (Zhang and Vigne, 2021). Ghosal et al. (2019) pointed out that environmental regulation can bring about changes in environmental conditions but may impose unnecessary production costs, thereby limiting corporate productivity. Zhang and Vigne (2021) also found that the financing and emission reduction policy represented by green credit has a punitive effect on the corporate total factor productivity, profitability, and sales growth of high-polluting firms. Furthermore, Albrizio et al. (2017) and He et al. (2020) concluded that the environmental regulation costs exceed the benefits that they bring and negatively affect corporate productivity.

Different from the compliance cost theory, Porter and Van der Linde (1995) indicated that, if environmental laws and regulations are well designed, they can achieve the effect of stimulating corporate innovation, thereby compensating for some or all of the additional compliance costs and creating a win-win situation for the economy and the environment. Lanoie et al. (2008) research on the relationship between strict environmental regulations and total factor productivity in Quebec, Canada, supported Porter's hypothesis. Furthermore, Greenstone and List (2012) found that, although environmental regulations increase the constraints on corporate loans, firms will innovate and improve their resource allocation efficiency in the process to make up for the environmental regulation cost. Ciabuschi et al. (2012) and Jiang et al. (2018) showed that a strict and standardized environmental supervision policy can stimulate firms' willingness to carry out environmental innovation and further increase corporate productivity. Similarly, Yang et al. (2012) found that the environmental regulations in Taiwan Province have generated more R&D investment and stimulated industrial productivity.

This paper aims to explore the impact of the green credit policy on corporate total factor productivity with the help of the exogenous shock of China's 2012 "Green Credit Guidelines." Against the current background of conserving resources and protecting the environment to promote sustainable and healthy economic development, heavily polluting firms must carry out certain transformations and upgrades from a long-term perspective. The implementation of the "Green Credit Guidelines" in 2012 marks the further standardization and institutionalization of China's green credit policy. The strengthening of the information-sharing mechanism has put firms under pressure from banks to cancel credit and government environmental penalties (Hu et al., 2021). The green credit policy has imposed stricter credit constraints on heavily polluting firms due to the increased loan threshold (Su and Lian, 2018; Xu and Li, 2020). Heavily polluting firms may face the risk of being forced to reduce their production or shut down some businesses, not only reducing their operating profit but also inducing a series of sunk costs (Qi et al., 2018). To change this situation, heavily polluting firms are more likely to develop new technical facilities and improve the production efficiency of normal projects to gain a competitive advantage and social reputation, changing the pressure dilemma that they face (Zhang et al., 2020c). Thus, we propose the first hypothesis:

H1: The implementation of the green credit policy significantly improves corporate total factor productivity of heavily polluting firms.

The green credit policy plays a role mainly through financial institutions, such as banks, by imposing credit constraints on financing firms. Therefore, the influence of green credit on TFP may be different for firms with different characteristics, with different external monitoring mechanisms, and in different regions (Cai et al., 2020).

Chinese firms have unique ownership characteristics, and the control rights of many firms are ultimately owned by the state. Compared with non-state-owned enterprises (non-SOEs), state-owned enterprises (SOEs) undertake more political tasks and non-market functions; thus, they may receive extra compensation from the government. SOEs generally have environmental "soft constraints" because they are easily favored by the government's "paternalism," which lowers the cost of environmental violations for SOEs. In addition, the banking system, dominated by state-owned banks, makes banks exert less supervision over SOEs (Firth et al., 2008), making it easier for SOEs to obtain bank loans. However, non-state-owned enterprises need to bear higher environmental costs, and they are faced with stronger banking supervision and greater financing constraints. In the face of green credit policy shocks, non-SOEs face stronger survival pressure than SOEs. In terms of firm size, large-scale firms usually have a stronger reputation and better social credit, and they have more mortgage assets and sufficient liquidity assets (Petersen and Rajan, 2017). Therefore, when faced with the increased financing constraints imposed by the green credit policy, they can supplement their working capital by means of commercial credit and cash on hand to alleviate the financing constraints. In contrast, small-scale firms may face stronger financing constraints because of their limited financing channels. Therefore, the green credit policy may impose greater policy constraints on non-SOEs and small-scale firms.

In addition, the external monitoring mechanisms may cause the effect of the green credit policy to differ. Studies have found that higher external monitoring quality contributes to higher corporate governance (Huson, 1997) and reduces managers' opportunistic behavior (Cheng et al., 2020). Thus, firms with strong external monitoring mechanisms have higher operating efficiency, and it is not easy for banks to restrain firms' financing further and play the governance role. On the contrary, in firms with weak external governance, the financial constraints imposed by financial institutions have stronger impacts on firms' production and operation activities. Therefore, green credit may promote banks to play the supervisory role in firms with weak external monitoring, improve their technological innovation and resource allocation efficiency, and then promote the improvement of these firms' total factor productivity.

The degree of financial development, government intervention, and resource allocation are different in different regions. Eastern Chinese regions have a higher financialization level and more efficient local governments; thus, the degree of marketization and the independence of the banking system are higher, a situation that is conducive to the implementation of the green credit policy. In addition, eastern Chinese regions have a better and systematic regional innovation environment. Efficient local governments provide firms with beneficial support, which helps them to reduce the uncertainty of the external environment and guides them to invest more in technological innovation (La Porta et al., 2002). Therefore, the better market and external environment of the eastern region may increase firms' output efficiency.

Based on the above analysis, we propose the following hypotheses:

H2a: The effect of the green credit policy on corporate TFP is more obvious in non-SOEs and small-scale firms.

H2b: The effect of the green credit policy on corporate TFP is more obvious in firms with weak external monitoring mechanisms.

H2c: The effect of the green credit policy on corporate TFP is more obvious in firms located in eastern China.

With the government's further strengthening of environmental governance, heavily polluting firms are faced with administrative interventions, such as large pollution taxes, huge penalties, withdrawal orders, suspension of production, and closure. These consequences urge them to reconsider their future financial situation and market development prospects and choose their investments more carefully. Therefore, after the implementation of the policy, the environmental compliance costs faced by heavily polluting firms may increase and the survival pressure may be aggravated. To achieve a longer-term survival goal, firms might have stronger motivation to improve their production technology and reduce their costs and pollutant emissions, thus choosing to ameliorate their technological innovation (Hu et al., 2020). Technological innovation promotes the increase of corporate patented and non-patented technologies, thus improving firms' knowledge stock. Under the action of a series of intermediary factors, firms' knowledge stock may be transformed into production capacity and finally improve corporate total factor productivity (Griliches, 1986; Medda and Piga, 2014). In addition, facing the supervision of banks, firms might reconsider their resource allocation in the production process, reducing the input of inefficient departments and increasing the input of efficient departments, to enhance its effectiveness. Higher resource allocation efficiency enables scale economies to be well utilized and contributes to the increase of corporate TFP (Goto and Suzuki, 1989; Bronwyn and Jacques, 1995). Thus, we propose our third hypothesis:

H3: The green credit policy improves corporate total factor productivity by promoting technological innovation and resource allocation efficiency.

3. Research design

3.1. Data

Using the "Green Credit Guidelines" implemented in the Chinese market in 2012 as a natural experiment, we adopt the DIDs approach to explore the influence of the green credit policy on total factor productivity. The initial samples are selected from all A-share public companies. Since the Guidelines were officially released on February 24, 2012, we set the 4 years before and after the implementation of the Guidelines, namely the years 2008–2015, as the sample research period. The data adopted in this paper include financial data and industrial pollutant emission data from the China Stock Market and Accounting Research (CSMAR) database, China Environmental Statistics Yearbook, and China Research Data Service Platform (CNRDS), respectively. We exclude financial firms, ST firms, and firms with missing research variables. Meanwhile, avoiding the interference of outliers in the sample regression results, we winsorize all the continuous variables at the 1% level at both tails and cluster all the standard errors of the regression results at the firm level. Finally, we obtain 8,632 firm-year observations.

3.2. Variables

3.2.1. Total factor productivity (TFP)

For measuring TFP, the OP method and LP method, constructed by Olley and Pakes (1996) and Levinsohn and Petrin (2003), respectively, have been well established in existing studies (Lian, 2012; Liu et al., 2021). Essentially, the OP method adopts the corporate current investment as a proxy for the productivity impact, but its assumption requires the relationship between the proxy variable (investment) and the total output always to remain monotonous, which means that it is impossible to estimate samples with zero investment. However, not every firm has positive investment every year, so a large sample of firms is missing from the estimation process. The LP method provides a new way to estimate TFP. Specifically, it uses intermediate inputs instead of investment as the proxy. It is easier to obtain the intermediate inputs, which enables researchers to select proxy variables flexibly based on the existing data. Therefore, we adopt corporate TFP based on the LP method, while we also calculate TFP based on the OP method in the robustness test.

Following Lian (2012) and Liu et al. (2021), the model for estimating TFP is as follows:

$$LnY_{i,t} = \beta_{0,t} + \beta_{1,t}LnK_{i,t} + \beta_{2,t}LnL_{i,t} + \beta_{3,t}LnM_{i,t} + \varepsilon_{i,t} \tag{1}$$

where the industrial added value ($Y_{i,t}$) is calculated using the sales; the capital ($K_{i,t}$) is calculated with the net value of fixed assets; the labor ($L_{i,t}$) is calculated as the number of employees; the intermediate inputs ($M_{i,t}$) are calculated as the cash paid for goods and services; and $\varepsilon_{i,t}$ represents TFP. We use Eq. (1) to carry out semi-parametric regression and ACF correction[7] to calculate the residuals, that is, corporate total factor productivity.

3.2.2. Independent variable

The 2012 Guidelines point out that banks are required to implement differentiated credit policies. Meanwhile, they should provide more sufficient credit resources and preferential interest rates for the green industries supported by the state, while they should reduce the loan line or increase the loan interest rates for heavily polluting industries, which are not encouraged or are even restricted by the state. Therefore, compared with other firms, heavily polluting firms face stronger regulatory pressure. The implementation of this policy has a stronger deterrent influence on heavily polluting firms.

Following Li et al. (2020), according to the Catalogue of Environmental Protection Certification Industry Classification Management of Listed Firms released by the Environmental Protection Administration in China in 2010, industries including steel, electrolytic aluminum, thermal power, cement, coal, metallurgy, petrochemicals, chemicals, paper making, building materials, pharmaceuticals, fermentation, brewing, leather, textiles, and mining are defined as heavily polluting industries. Furthermore, in accordance with the classification standard[8] of the industry classification guidelines for public firms issued by the CSRC in 2001, if a public firm belongs to the above 16 heavily polluting industries, we allocate it to the treatment group and $Treat_i$ equals 1, and, if a public firm does not belong to the above 16 heavily polluting industries, we class it into the control group and $Treat_i$ equals 0.

Since the Guidelines were issued on February 24, 2012, $Post_t$ is a year dummy variable that equals 1 if the observation year is from 2012 to 2015 and 0 if the observation year is from 2008 to 2011. $Treat_i * Post_t$ is the main test independent variable in this paper. The coefficient of $Treat_i$

[7] Ackerberg et al. (2015) pointed out that a problem of "function correlation" may exist when using the semi-parametric method to estimate TFP. Therefore, we perform the ACF correction in the semi-parametric regression to estimate robust results.

[8] According to the industry classification guidelines of 2001, the industry codes referring to firms in heavily polluting industries are B01,B03,B05,B07, C01,C03,C05,C11,C14,C31,C35,C41,C43,C61,C65,C67,C81, D01,H01,and H03.

$* Post_t$ indicates that, after the implementation of the green credit policy, compared with the control group, the TFP in treatment group has changed, which directly reflects the effect of the green credit policy.

3.3. Models

The following DIDs model is adopted to test the impact of green credit on corporate total factor productivity:

$$TFP_{i,t} = \beta_0 + \beta_1 Treat_i * Post_t + \beta_2 Post_t + \beta_3 Treat_i + \sum_k \gamma_k Control_{k,i,t} + \sum Industry + \sum Year + \varepsilon_{i,t} \quad (2)$$

where $Treat_i$ equals 1 when firm i is a heavily polluting firm and 0 otherwise; $Post_t$ is a year dummy variable that equals 1 if the observation year is from 2012 to 2015 and 0 if the observation year is from 2008 to 2011. Following Ling et al. (2020), $Control_{k,i,t}$ contains the firm size ($Size_{i,t}$), leverage ratio ($Lev_{i,t}$), return on total assets ($Roa_{i,t}$), fixed asset ratio ($Fixs_{i,t}$), firm growth ($Growth_{i,t}$), capital labor ratio ($Klratio_{i,t}$), firm age ($Age_{i,t}$), and shareholding ratio of the largest shareholder ($Frs_{i,t}$); *ΣIndustry* and *ΣYear* indicate that we control for industry and year fixed effects. β_1, the coefficient for $Treat_i * Post_t$, is the DIDs effect, which measures the influence of the green credit policy on the corporate total factor productivity of heavily polluting firms.

4. Empirical results

4.1. Descriptive statistics

Table 1 presents the descriptive statistical results. The mean value of total factor productivity $TFP_{i,t}$ is 9.890, and the standard deviation is 0.905, which is similar to the estimates reported by Tang et al. (2020). These results reveal that the total factor productivity of different firms in the sample period is quite different. The mean value of the experimental variable $Treat_i$ is 0.361, which indicates that 36.1% of the firms in the sample are classified as heavily polluting firms and 63.9% of the firms are classified as non-heavily polluting firms. In addition, the results for the other variables are in line with the existing literature (e.g.,).

4.2. Correlation analysis

Table 2 reports the Pearson and Spearman correlation coefficient matrix. The correlation coefficients between $TFP_{i,t}$ and $Treat_i * Post_t$ are 0.065 and 0.051, respectively. In addition, they are significant at the 1% significance level, supporting *Hypothesis 1*. Further, we calculate the variance inflation factor (VIF) between the core independent variable and the other control variables to test whether there is a serious collinearity problem. We find that the biggest value is 2.57, which is below 10, the critical value of the multicollinearity problem (Kennedy, 2008). Therefore, there is no multicollinearity problem between the independent variable and the control variables in our paper.

Table 1
Descriptive Statistics Table 1 shows the results of descriptive statistics. The sample includes all A-share listed firms from 2008 to 2015. We report the mean, standard deviation, minimum, median, and maximum for each variable. Detailed descriptions of all variables are presented in the Appendix. All continuous variables are winsorized at the 1% level in both tails.

Variable	Obs	Mean	Std.dev.	Minimum	Median	Maximum
$TFP_{i,t}$	8,632	9.890	0.905	8.040	9.778	12.550
$Post_t$	8,632	0.500	0.500	0	0.500	1
$Treat_i$	8,632	0.361	0.480	0	0	1
$Size_{i,t}$	8,632	22.120	1.313	19.410	21.970	25.990
$Lev_{i,t}$	8,632	0.509	0.200	0.074	0.516	0.953
$Roa_{i,t}$	8,632	0.036	0.056	-0.184	0.0310	0.204
$Fixs_{i,t}$	8,632	0.266	0.187	0.002	0.235	0.762
$Growth_{i,t}$	8,632	0.170	0.511	-0.574	0.091	3.741
$Klratio_{i,t}$	8,632	12.660	1.162	9.982	12.570	16.120
$Age_{i,t}$	8,632	2.776	0.291	1.946	2.833	3.332
$Frs_{i,t}$	8,632	0.367	0.155	0.088	0.350	0.759

4.3. Univariate analysis

The univariate analysis is reported in Table 3. After the implementation of the green credit policy, the mean of $TFP_{i,t}$ increased by 0.125 for the treatment group, and it is significant at the 1% significance level, while the mean of $TFP_{i,t}$ increased by 0.048 for the control group, but it is not significant. This result reveals that the implementation of the green credit policy clearly improved the TFP of heavily polluting firms, and the policy effect is 0.077, which is significant at the 10% significance level.

4.4. Empirical results

Table 4 shows the main empirical results based on Eq. (2). Column (1) presents the results controlling for the industry and year fixed effects without any control variable. The coefficient of $Treat_i * Post_t$ is 0.077 (t value = 2.45) and is significant at the 5% significance level. Column (2) reports the result with the control variables; the coefficient of $Treat_i * Post_t$ is 0.075 (t value = 2.91) and is significant at the 1% level. The results reflect that the green credit policy in China significantly improves the corporate total factor productivity of listed firms, supporting *Hypothesis 1*. Furthermore, the coefficients of the control variables are consistent with the previous literature. For example, the coefficient of $Size_{i,t}$ is significantly positive at the 1% significance level, which suggests that the larger firms' scale, the higher their TFP, in line with Tang et al. (2020). We also observe that the coefficients of $Lev_{i,t}$, $Klratio_{i,t}$, $Growth_{i,t}$, and $Roa_{i,t}$ are positively associated with corporate TFP, which suggests that firms with high leverage ratios, a high capital labor ratio, a high growth rate, and high returns tend to increase TFP in China, consistent with Cai et al. (2020) and Liu et al. (2021).

5. Robustness checks

We perform a series of robustness checks, including an effectiveness test of the green credit policy, parallel trend test, placebo test, PSM-DID test, excluding the impact of other contemporary policies, replacing indicators, and controlling for the impact of macroeconomic factors, to verify our baseline results further.

5.1. Policy effectiveness test

The effectiveness of the green credit policy is the premise for our research results. Since China's green credit policy mainly restricts the financing scale of firms through bank loans, we first test the changes in the scale of corporate bank loans before and after the implementation of the Guidelines.

We first test the change trend of the bank loan scale of heavily polluting firms and non-heavily polluting firms around 2012. Following Su et al. (2018), we measure the bank loan scale of firms, which is

Table 2
Correlation coefficient Matrix Table 2 reports the Pearson (below diagonal) and Spearman (above diagonal) correlation coefficient matrix. *, **, and *** indicate 10%, 5%, and 1% significance level, respectively. Detailed descriptions of all variables are presented in the Appendix. All continuous variables are winsorized at the 1% level in both tails.

	TFPi,t	Treati * Postt	Postt	Treati	Sizei,t	Levi,t	Roai,t	Fixsi,t	Growthi,t	Klratioi,t	Agei,t	Frsi,t
$TFP_{i,t}$	1	0.051***	0.061***	-0.138***	0.365***	0.253***	0.148***	-0.478***	0.172***	-0.027**	0.087***	0.162***
$Treat_i$ * $Post_t$	0.065***	1	0.469***	0.625***	0.152***	0.001	-0.083***	0.217***	-0.149***	0.199***	0.148***	0.017
$Post_t$	0.056***	0.469***	1	0.000	0.226***	0.007	-0.121***	-0.051***	-0.208***	0.053***	0.428***	-0.028***
$Treat_i$	-0.157***	0.625***	-0.000	1	0.089***	0.003	-0.034***	0.375***	-0.022**	0.248***	-0.093***	0.051***
$Size_{i,t}$	0.358***	0.154***	0.216***	0.094***	1	0.406***	-0.042***	0.046***	0.021*	0.308***	0.120***	0.257***
$Lev_{i,t}$	0.250***	-0.000	0.003	0.003	0.387***	1	-0.417***	-0.011	0.053***	0.085***	0.073***	0.079***
$Roa_{i,t}$	0.151***	-0.056***	-0.093***	0.003	-0.003	-0.404***	1	-0.137***	0.309***	-0.133***	-0.108***	0.076***
$Fixs_{i,t}$	-0.455***	0.208***	-0.042***	0.352***	0.104***	0.033***	-0.149***	1	-0.071***	0.597***	-0.112***	0.046***
$Growth_{i,t}$	0.161***	-0.089***	-0.107***	-0.047***	-0.001	0.062***	0.189***	-0.070***	1	-0.054***	-0.130***	0.032***
$Klratio_{i,t}$	-0.023**	0.187***	0.043***	0.234***	0.330***	0.084***	-0.094***	0.616***	-0.036***	1	0.017	0.093***
$Age_{i,t}$	0.092***	0.161***	0.431***	-0.076***	0.105***	0.082***	-0.097***	-0.083***	-0.037***	0.025**	1	-0.223***
$Frs_{i,t}$	0.172***	0.019*	-0.028**	0.054***	0.285***	0.077***	0.090***	0.052***	0.066***	0.115***	-0.209***	1

Table 3
Univariate analysis Table 3 presents the results of univariate analysis on the differences of total factor productivity *(TFP)* between the treatment group (heavily polluting firms) and the control group (non-heavily polluting firms) before and after the green credit policy in 2012. *, **, and *** indicate 10%, 5%, and 1% significance level, respectively.

$TFP_{i,t}$	Treatment (1)	Control (2)	Differences (1) - (2)	*t*-Test (1) – (2)
2008 - 2011 (a)	9.661	9.987	-0.326	-9.788***
2012 - 2015 (b)	9.786	10.035	-0.249	-7.786***
Diff (b) - (a)	0.125	0.048	0.077	1.66*
t - Test (b) - (a)	4.268***	1.568		

calculated as the ratio of the sum of the short-term loans, the long-term loans, and the balance of long-term loans due within 1 year to the total assets of the firm, and we use it to drawFigure 2.

Figure 2 presents the change trend of the average bank loan scale of heavily polluting firms and non-heavily polluting firms from 2008 to 2015; the blue solid line represents the treatment group (heavily polluting firms) and the red dotted line represents the control group (non-heavily polluting firms). Figure 2 shows that, from 2008 to 2011, the bank loan scale of the treatment group and the control group basically maintained the same change trend, and the bank loan scale of the treatment group was significantly higher than that of the control group. However, after the implementation of the Guidelines in 2012, the bank loan scale of the treatment group decreased significantly while the bank loan scale of the control group did not change significantly. It can be judged from the change trend that, following the implementation of the Guidelines in 2012, the bank loan scale of heavily polluting firms is obviously constrained; thus, the effectiveness of the green credit policy in 2012 can be verified preliminarily.

Furthermore, we employ the DIDs approach to explore the impact of the green credit policy on the scale of bank loans ($Bankloan_t$), new loans ($\triangle Loan_t$), new short-term loans ($\triangle SLoan_t$), and new long-term loans ($\triangle LLoan_t$).[9] Table 5 shows the results. Column (1) presents the results of the impact of the green credit policy on the scale of bank loans, controlling for year fixed effects and industry fixed effects. We find that the coefficient of $Treat_i$ * $Post_t$ is -0.017 (t = -3.25), which is significant at the 1% significance level. This result indicates that the implementation of the green credit policy in 2012 significantly reduced the bank loan scale of heavily polluting firms. From Columns (2), (3), and (4), we find that new loans, new short-term loans, and new long-term loans of heavily polluting firms significantly reduced after the implementation of the green credit policy. Overall, the results show that the implementation of the green credit policy in 2012 has reduced the bank loan scale of heavily polluting firms and exerted the desired policy effect.

Table 4
The impact of green credit policy on total factor productivity Table 4 reports the results of green credit policy affecting the corporate total factor productivity. $Treat_i$ is a dummy variable that equals 1 if the firm belongs to heavily polluting firms, and 0 is the firm belongs to non-heavily polluting firms. $Post_t$ is a year dummy variable that equals 1 if the observation year is from 2012 to 2015, and 0 if the observation year is from 2008 to 2011. $TFP_{i,t}$ is the indicator of corporate total factor productivity. Controlling for industry fixed effects and year fixed effects, Column (1) presents the results without control variables while Column (2) presents the results with control variables. Detailed descriptions of all variables are presented in the Appendix. *t*-value are presented in the parentheses and *, **, and *** indicate 10%, 5%, and 1% significance level, respectively.

Dependent variable	$TFP_{i,t}$ (1)	$TFP_{i,t}$ (2)
$Treat_i$ * $Post_t$	0.077**	0.075***
	(2.45)	(2.91)
$Post_t$	0.102***	-0.123***
	(3.75)	(-3.17)
$Treat_i$	-0.125**	-0.051
	(-2.53)	(-1.32)
$Size_{i,t}$		0.173***
		(10.89)
$Lev_{i,t}$		0.665***
		(6.39)
$Roa_{i,t}$		2.387***
		(9.73)
$Fixs_{i,t}$		-2.474***
		(-20.48)
$Growth_{i,t}$		0.143***
		(8.37)
$Klratio_{i,t}$		0.229***
		(10.70)
$Age_{i,t}$		0.019
		(0.27)
$Frs_{i,t}$		0.545***
		(4.85)
Constant	9.261***	2.882***
	(94.61)	(7.93)
Observations	8,632	8,632
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Adjusted R^2	0.244	0.530

[9] Following Liu and Cao (2018), $\triangle Loan_t$ is calculated as the increment of the corporate bank loans divided by the total assets; $\triangle SLoan_t$ is calculated as the increment of the short-term loans divided by the total assets; and $\triangle LLoan_t$ is calculated as the increment of the long-term loans divided by the total assets.

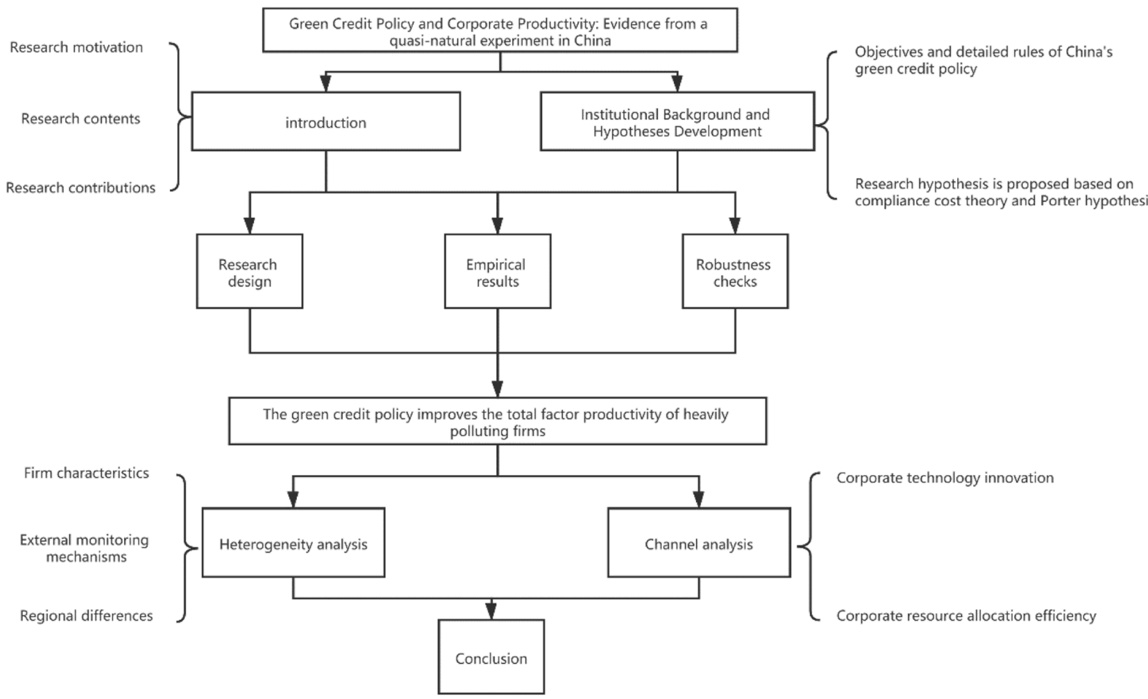

Figure 1. Research framework of this paper Figure 1 presents this paper's research framework.

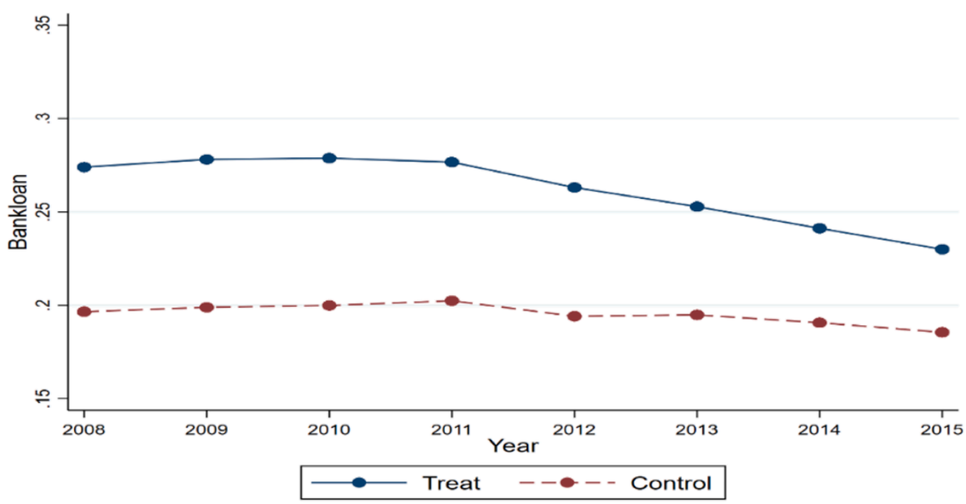

Figure 2. Change trend of firm bank loan scale Figure 2 presents the change trend of the average bank loan scale of the treatment group (heavily polluting firms) and the control group (non-heavily polluting firms) from 2008 to 2015, in which the blue solid line represents the treatment group (heavily polluting firms) and the red dotted line represents the control group (non-heavily polluting firms). The bank loan scale (*Bankloan*$_t$) is calculated by the ratio of the sum of the short-term loans, the long-term loans, and the balance of long-term loans due within one year to the total assets of the firm.

5.2. Parallel trends analysis

The treatment group and control group should meet the parallel trend assumption in the DIDs model; that is, before the implementation of the green credit policy, the total factor productivity of heavily polluting firms and non-heavily polluting firms should have common trends.

To verify the parallel trends assumption, following Serfling (2016) and Dessaint et al. (2017), we construct year dummies tracking the effect of the green credit policy in 2012. *Pre_year3/2/1* is a dummy that equals 1 if the observation year is 2009/2010/2011, respectively, and 0 otherwise. *Post_year1/2/3/4* is a dummy that equals 1 if the observation year is 2012/2013/2014/2015, respectively, and 0 otherwise. We multiply *Pre_year3/2/1* and *Post_year1/2/3/4* with *Treat*, respectively, and obtain *Pre_3, Pre_2, Pre_1* and *Post_1, Post_2, Post_3, Post_4*. Then, we re-estimate Eq. (2) with *Pre_3, Pre_2, Pre_1* and *Post_1, Post_2, Post_3, Post_4* to examine the parallel trends hypothesis.

The results of the parallel trends test are presented in Table 6. The coefficients of *Pre_3, Pre_2*, and *Pre_1* are positive, but they are not significant, which indicates that there is no clear distinction in the change trends of TFP in the treatment group and the control group before the implementation of the green credit policy. However, after the green credit policy, we find that the coefficients of *Post_1, Post_2, Post_3*, and *Post_4* are all significantly positive at the 1% significance level, indicating that green credit policy can significantly enhance the TFP of heavily polluting firms.

Figure 3 plots the coefficient estimation results in Table 6 under the 95% confidence interval; the dashed column represents the confidence interval, and the circle represents the estimated coefficient value. Figure 3 shows that, although the coefficient estimation results of variables *Pre_3, Pre_2*, and *Pre_1* before the green credit policy are positive, they are not significant. This shows that the treatment group and the control group satisfy the parallel trends hypothesis.

Table 5

Robustness check: Policy effectiveness test Table 5 shows the results of the impact of green credit policy affecting firm loan scale. $Treat_i$ is a dummy variable that equals 1 if the firm belongs to heavily polluting firms, and 0 is the firm belongs to non-heavily polluting firms. $Post_t$ is a year dummy variable that equals 1 if the observation year is from 2012 to 2015, and 0 if the observation year is from 2008 to 2011. $Bankloan_t$ is calculated by the ratio of the sum of the short-term loans, the long-term loans, and the balance of long-term loans due within one year to the total assets of the firm. $\triangle Loan_t$ is calculated by the increment of firm bank loans divided by total assets; $\triangle SLoan_t$ is calculated by the increment of the short-term loans divided by the total assets; $\triangle LLoan_t$ is calculated by the increment of long-term loans divided by total assets. Detailed descriptions of all variables are presented in the Appendix. *t*-value are presented in the parentheses and *, **, and *** indicate 10%, 5%, and 1% significance level, respectively.

Dependent variables	$Bankloan_t$ (1)	$\triangle Loan_t$ (2)	$\triangle SLoan_t$ (3)	$\triangle LLoan_t$ (4)
$Treat_i * Post_t$	-0.017***	-0.015***	-0.007**	-0.007***
	(-3.25)	(-3.81)	(-2.42)	(-2.96)
$Post_t$	-0.026***	-0.010**	-0.002	-0.003
	(-3.86)	(-2.33)	(-0.66)	(-1.35)
$Treat_i$	0.049***	0.014***	0.007***	0.005***
	(6.56)	(4.23)	(2.97)	(3.16)
$Size_{i,t}$	-0.001	0.002	0.000	0.000
	(-0.29)	(1.54)	(0.31)	(0.88)
$Lev_{i,t}$	0.523***	0.081***	0.040***	0.029***
	(29.65)	(10.18)	(7.48)	(8.17)
$Roa_{i,t}$	-0.275***	-0.048**	-0.032	-0.008
	(-6.89)	(-2.03)	(-1.61)	(-0.68)
$Fixs_{i,t}$	0.100***	-0.067***	-0.027***	-0.031***
	(4.79)	(-8.65)	(-5.57)	(-7.17)
$Growth_{i,t}$	0.001	0.028***	0.015***	0.011***
	(0.19)	(9.61)	(7.71)	(6.09)
$Klratio_{i,t}$	0.023***	0.008***	0.004***	0.002***
	(6.67)	(6.09)	(4.45)	(3.22)
$Age_{i,t}$	-0.019*	-0.018***	-0.012***	-0.004**
	(-1.69)	(-4.64)	(-4.86)	(-2.04)
$Frs_{i,t}$	-0.042**	0.005	0.004	0.002
	(-2.39)	(0.71)	(0.92)	(0.57)
Constant	-0.222***	-0.096***	-0.021	-0.030**
	(-3.29)	(-3.88)	(-1.33)	(-2.32)
Observations	8,479	8,337	8,632	8,571
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.587	0.107	0.046	0.061

Table 6

Robustness check: Parallel trends analysis Table 6 shows the results of parallel trends analysis. *Treat* is a dummy variable that equals 1 if the firm belongs to heavily polluting firms, and 0 is the firm belongs to non-heavily polluting firms. We construct year dummies tracking the effect of the green credit policy in 2012. *Pre_year3/2/1* is a dummy that equals 1 if the observation year is 2009/2010/2011, respectively, and 0 otherwise. *Post_year1/2/3/4* is a dummy that equals 1 if the observation year is 2012/2013/2014/2015, respectively, and 0 otherwise. We multiply *Pre_year3/2/1, Post_year1/2/3/4* with *Treat*, respectively, and get *Pre_3, Pre_2, Pre_1*, and *Post_1, Post_2, Post_3, Post_4*. Detailed descriptions of all variables are presented in the Appendix. *t*-value are presented in the parentheses and *, **, and *** indicate 10%, 5%, and 1% significance level, respectively.

Dependent variable	$TFP_{i,t}$
Pre_3	0.031
	(1.12)
Pre_2	0.009
	(0.32)
Pre_1	0.048
	(1.52)
Post_1	0.091***
	(3.23)
Post_2	0.097***
	(3.45)
Post_3	0.091***
	(3.23)
Post_4	0.062**
	(2.20)
$Size_{i,t}$	0.167***
	(17.92)
$Lev_{i,t}$	0.242***
	(5.74)
$Roa_{i,t}$	1.961***
	(19.51)
$Fixs_{i,t}$	-2.242***
	(-41.88)
$Growth_{i,t}$	0.174***
	(21.94)
$Klratio_{i,t}$	0.195***
	(24.44)
$Age_{i,t}$	0.061
	(1.09)
$Frs_{i,t}$	0.271***
	(4.25)
Constant	3.700***
	(14.83)
Observations	8,632
Industry Fixed Effects	Yes
Year Fixed Effects	Yes
Adjusted R^2	0.350

5.3. Placebo test

To avoid the possibility that the regression results are driven by false correlation or time-varying factors, following Chen et al. (2018), we carry out a placebo test by artificially changing the policy year. First, we assume 2009 as the policy year, and $Post_t$ is a year dummy variable that equals 1 if the observation year is from 2009 to 2012 and 0 if the observation year is from 2004 to 2008. Then, we assume 2014 as the policy year, and $Post_t$ is a year dummy variable that equals 1 if the observation year is from 2014 to 2017 and 0 if the observation year is from 2010 to 2013. We re-estimate Eq. (2) with the new $Post_t$, respectively.

The results are reported in Table 7. The coefficients of $Treat_i * Post_t$ are not significant, regardless of whether the policy year moves forward or backward, which implies that the virtual policy has no effect on corporate TFP and the quasi-natural experimental environment selected in this paper is relatively ideal.

5.4. PSM-DID

To avoid the sample selection bias caused by other firm characteristics, following Bowen et al. (2010) and Yuan et al. (2016), we use the propensity score matching (PSM) method to reconstruct the control group to reduce the estimation error caused by selection bias. First, we take $Treat_i$ as the dependent variable and a series of variables, including firm size ($Size_{i,t}$), return on assets ($Roa_{i,t}$), proportion of fixed assets ($Fixs_{i,t}$), growth ($Growth_{i,t}$), capital labor ratio ($Klratio_{i,t}$), listing age ($Age_{i,t}$), and shareholding ratio of the largest shareholder ($Frs_{i,t}$), as the matching variables to conduct logit regression, controlling for year fixed effects and industry fixed effects, and obtain the propensity score. Then, based on the propensity score, 1:1 nearest neighbor matching is performed to find other firms that match the firm characteristics in the treatment group. Table 8 reports the results after using the PSM-DID method, and we find that the coefficient of $Treat_i * Post_t$ is still significantly positive, indicating that our result is robust.

5.5. Excluding the impact of other contemporary policies

Although our focus is on the Green Credit Guidelines implemented in 2012, other policies in the same period may also exert impacts on our estimation results. The most likely interference would stem from the "emissions trading system" and the "China Five-Year Plan" industrial policy. Therefore, in this section, we test the impact of these two policies on our estimation results.

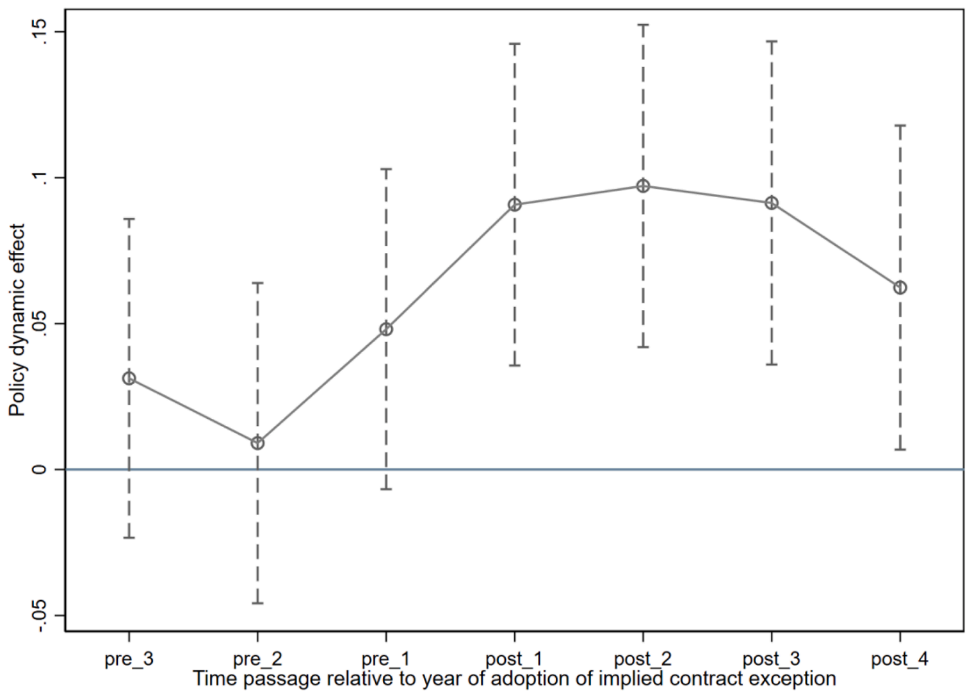

Figure 3. Parallel trends analysis Figure 3 reports the test coefficients of parallel trend assumption under the 95% confidence interval, where the dashed column represents the confidence interval, and the circle represents the estimated coefficient value. *Treat* is a dummy variable that equals 1 if the firm belongs to heavily polluting firms, and 0 is the firm belongs to non-heavily polluting firms. We construct year dummies tracking the effect of the green credit policy in 2012. *Pre_year3/2/1* is a dummy that equals 1 if the observation year is 2009/2010/2011, respectively, and 0 otherwise. *Post_year1/2/3/4* is a dummy that equals 1 if the observation year is 2012/2013/2014/2015, respectively, and 0 otherwise. We multiply *Pre_year3/2/1, Post_year1/2/3/4* with *Treat*, respectively, and get *Pre_3, Pre_2, Pre_1*, and *Post_1, Post_2, Post_3, Post_4*. Total factor productivity (*TFP*) is the dependent variable, we estimate Eq (2) with *Pre_3, Pre_2, Pre_1*, and *Post_1, Post_2, Post_3, Post_4* and get the coefficient distribution of parallel trend analysis.

5.5.1. Emissions trading system

The emissions trading system is a means for the government to collect fees based on the external environmental losses caused by the discharge of pollutants and then realize the internalization of the external environmental costs of the pollutant-emitting unit.[10] With economic development, environmental problems have become increasingly apparent, and relatively serious air pollution has appeared in all provinces. Facing severe environmental problems, the "Outline of the Eleventh Five-Year Plan for the National Economic and Social Development of the People's Republic of China" clearly sets out the emission reduction target. During the "Eleventh Five-Year Plan" period, energy consumption per unit of GDP should be reduced by about 20% and the total discharge of major pollutants should be reduced by 10%. To achieve the pollutant emission reduction target, the State Council issued the "Plan" in May 2007 to double the SO_2 emission fee in the original pollutant collection fee.[11] From the perspective of environmental regulations, due to the increase in the SO_2 emission fee standard, the environmental costs faced by heavily polluting firms increase further and impose certain cost pressures on them. Thus, heavily polluting firms may choose to engage in technological innovation and reallocate factors of production due to the influence of the emissions trading system, which in turn may affect their total factor productivity.

Since the increase in the SO_2 emission fee standard coincides with the sample interval studied in this paper, it may have impacts on our results. Therefore, we should control the impact of the emissions trading system. Specifically, after the 2007 policy, provinces adjusted their corresponding charging standards in different years. Among them, 15 provinces[12] had completed the adjustments to their pollution discharge fees before 2015. Since the International Development and Reform Commission, the Ministry of Finance, and the Ministry of Environmental Protection jointly issued the "Notice on Adjusting Pollutant Discharge Fee Collection Standards and Other Related Issues" in September 2014, all provinces (municipalities) are required to adjust their SO_2 pollution discharge fees by the end of June 2015. The charging standard was adjusted to not less than 1.26 yuan per kilogram, and other provinces successively adjusted in 2015.

Following Guo et al. (2019), we introduce the emission standard adjustment status variable PDS_t and $PDS_t * Treat_i$ into Eq. (2). In addition, when the province where a firm is located has adjusted the SO_2 charging standard in year t, PDS_t equals 1 and otherwise 0. Column (1) in Table 9 shows the impact of the implementation of the green credit policy on total factor productivity after controlling for the effects of the emissions trading system. The results show that the coefficient of PDS_t is significantly positive at the 1% significance level, indicating that the increased SO_2 emissions fees significantly improve corporate total factor productivity. However, the coefficient of $PDS_t * Treat_i$ is insignificant, indicating that the emissions trading system does not have a differentiated impact on firms with different pollution levels. More importantly, the coefficient of $Treat_i * Post_t$ is still significantly positive at the 1% significance level, which shows that our result is not affected by the emissions trading system.

5.5.2. China Five-Year Plan industrial policy

As a macroeconomic policy, the industrial policy is an important way for the state to regulate and control the economy, and inevitably it affects the micro-level behavior of firms (Liu et al., 2021). Different from the effect of environmental regulations on corporate productivity, the industrial policy could increase the government support for corresponding industries. For example, fiscal and credit concessions can

[10] China's sewage charging system was first established in the form of the "Environmental Protection Law of the People's Republic of China (Trial)," promulgated in September 1979, and a trial collection of sewage charges was implemented in some provinces (municipalities).

[11] In 2003, the former National Development Planning Commission, the Ministry of Finance, the former State Environmental Protection Administration, and the former State Economic and Trade Commission jointly issued the "Sewage Discharge Fee Collection Standard Management Measures," which required the SO_2 discharge fee collection standards to be increased to 0.63 yuan per kilogram before July 1, 2005.

[12] Jiangsu, Anhui, Hebei, Shandong, Inner Mongolia, Guangxi, Shanghai, Yunnan, Guangdong, Liaoning, Tianjin, Xinjiang, Beijing, Ningxia, and Zhejiang.

Table 7
Robustness check: Placebo test Table 7 reports Placebo test results. First, we assume 2009 as the policy year, and $Post_t$ is a year dummy variable that equals 1 if the observation year is from 2009 to 2012, and 0 if the observation year is from 2004 to 2008. $Treat_i$ is a dummy variable that equals 1 if the firm belongs to heavily polluting firms, and 0 is the firm belongs to non-heavily polluting firms. Column (1) shows the results. Then, we assume 2014 as the policy year, and $Post_t$ is a year dummy variable that equals 1 if the observation year is from 2014 to 2017, and 0 if the observation year is from 2010 to 2013. $Treat_i$ is a dummy variable that equals 1 if the firm belongs to heavily polluting firms, and 0 is the firm belongs to non-heavily polluting firms. Column (2) shows the results. Detailed descriptions of all variables are presented in the Appendix. *t*-value are presented in the parentheses and *, **, and *** indicate 10%, 5%, and 1% significance level, respectively.

Dependent variable	$TFP_{i,t}$ (1)	$TFP_{i,t}$ (2)
$Treat_i * Post_t$	0.021	0.040
	(0.78)	(1.63)
$Post_t$	-0.104***	-0.111***
	(-2.70)	(-2.85)
$Treat_i$	-0.033	-0.024
	(-0.77)	(-0.64)
$Size_{i,t}$	0.173***	0.173***
	(10.88)	(10.88)
$Lev_{i,t}$	0.664***	0.665***
	(6.39)	(6.39)
$Roa_{i,t}$	2.380***	2.382***
	(9.69)	(9.71)
$Fixs_{i,t}$	-2.476***	-2.476***
	(-20.48)	(-20.49)
$Growth_{i,t}$	0.142***	0.143***
	(8.36)	(8.37)
$Klratio_{i,t}$	0.230***	0.230***
	(10.74)	(10.73)
$Age_{i,t}$	0.020	0.020
	(0.29)	(0.29)
$Frs_{i,t}$	0.546***	0.545***
	(4.86)	(4.85)
Constant	2.866***	2.864***
	(7.88)	(7.89)
Observations	8,632	8,632
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Adjusted R^2	0.529	0.529

Table 8
Robustness check: PSM-DID Table 8 reports the results of PSM-DID approach. According 1:1 nearest neighbor matching, we get the new sample. $Treat_i$ is a dummy variable that equals 1 if the firm belongs to heavily polluting firms, and 0 is the firm belongs to non-heavily polluting firms. $Post_t$ is a year dummy variable that equals 1 if the observation year is from 2012 to 2015, and 0 if the observation year is from 2008 to 2011. Detailed descriptions of all variables are presented in the Appendix. *t*-value are presented in the parentheses and *, **, and *** indicate 10%, 5%, and 1% significance level, respectively.

Dependent variable	$TFP_{i,t}$
$Treat_i * Post_t$	0.071***
	(2.59)
$Post_t$	-0.141***
	(-3.29)
$Treat_i$	-0.053
	(-1.35)
$Size_{i,t}$	0.180***
	(10.56)
$Lev_{i,t}$	0.487***
	(4.40)
$Roa_{i,t}$	2.228***
	(8.63)
$Fixs_{i,t}$	-2.306***
	(-17.92)
$Growth_{i,t}$	0.152***
	(7.71)
$Klratio_{i,t}$	0.255***
	(11.06)
$Age_{i,t}$	-0.001
	(-0.01)
$Frs_{i,t}$	0.413***
	(3.51)
Constant	2.556***
	(6.74)
Observations	6,944
Industry Fixed Effects	Yes
Year Fixed Effects	Yes
Adjusted R^2	0.513

alleviate the financing difficulties faced by firms and improve their financing capabilities. A change in the corporate financing environment has impacts on corporate investment activities, R&D investment, and total factor productivity (Aghion et al., 2015). The sample interval of this paper spans two five-year plans of China: the "Eleventh Five-Year Plan" and "Twelfth Five-Year Plan." The "Twelfth Five-Year Plan" clearly pointed out that "At this stage, the state focuses on cultivating and developing energy conservation and environmental protection, new generation information technology, biological high-end equipment manufacturing, new energy, new materials, new energy vehicles and other industries." The government's focused support may affect firms' preferences, including those for project approval, bank loans, and tax payments, as well as a direct inflow of financial subsidies, which may improve the resource allocation of firms and affect their total factor productivity.

Therefore, we should control the influence of the government's corresponding industry support. Following Chen et al. (2017), we regard industries linked to "key development," "vigorous development," "priority development," "key support," "bigger and stronger," "focus on training," and "pillar" in the "Twelfth Five-Year Plan" document as key industries and obtain the corresponding industry of the key industry. Then, we add the 12th Five-Year Plan industrial support variable IPN_i and the interaction term $IPN_i * P_t$ of the industrial support variable and the policy shock variable to Eq. (2). If the listed firm belongs to the above industries, IPN_i equals 1 and otherwise 0; P_t is a policy shock variable, which equals 1 if the observation year is after 2011[13] and 0 otherwise. The results are shown in Column (2) of Table 9. The coefficient of $Treat_i * Post_t$ is still significantly positive at the 1% significance level, indicating that our results are not affected by the government's industrial policy.

5.6. Change indicator

5.6.1. Changing the treatment group and the control group

Following Li and Tao (2012) and Ling et al. (2020), we reconstruct the treatment group and the control group by constructing the index of industrial pollution emissions intensity in 2011. The specific construction process is as follows.

First, we select four types of industrial pollution emissions, specifically industrial solid waste emissions, industrial smoke (dust) emissions, industrial wastewater emissions, and industrial sulfur dioxide emissions, to calculate the industrial pollution emissions per unit output value, as shown in Eq. (3):

$$UE_{i,j} = E_{i,j}/O_i \tag{3}$$

where $E_{i,j}$ represents the emissions of industrial major pollutant j and O_i represents the industrial total output value.

Then, adopting the method of Li and Tao (2012), we linearly standardize the industrial pollutant emissions per unit output value:

$$UE^s_{i,j} = \left[UE_{i,j} - \min(UE_j)\right] \Big/ \left[\max(UE_i) - \min(UE_j)\right] \tag{4}$$

[13] The 12th Five-Year Plan started in 2011.

Table 9

Robustness checks: Excluding the impact of other contemporary policies Table 9 reports the regression results of excluding the impact of other contemporary policies. Column (1) reports the results excluding the impact of emissions trading system. $PDS_{,t}$ is the emission standard adjustment status variable, which equals 1 when the province where the firm located has adjusted in year t, and 0 otherwise. Column (2) reports the results excluding the impact of China Five-year Plan industrial policy. IPN_i equals 1 if the listed firm belongs to the key industries, 0 otherwise. P_t is a policy shock variable, which equals 1 if the observation year after 2011, 0 otherwise.

Dependent variable	$TFP_{i,t}$ (1)	$TFP_{i,t}$ (2)
$Treat_i * Post_t$	0.106***	0.076***
	(3.43)	(2.96)
$Post_t$	-0.215***	-0.122***
	(-5.08)	(-3.08)
$Treat_i$	-0.029	-0.046
	(-0.71)	(-1.18)
PDS_t	0.171***	
	(4.73)	
$PDS_t * Treat_i$	-0.071	
	(-1.25)	
IPN_i		0.057
		(1.29)
$IPN_i * P_t$		-0.004
		(-0.16)
$Size_{i,t}$	0.171***	0.170***
	(10.88)	(10.76)
$Lev_{i,t}$	0.670***	0.659***
	(6.50)	(6.31)
$Roa_{i,t}$	2.345***	2.410***
	(9.67)	(9.81)
$Fixs_{i,t}$	-2.449***	-2.466***
	(-20.46)	(-20.32)
$Growth_{i,t}$	0.144***	0.143***
	(8.39)	(8.36)
$Klratio_{i,t}$	0.223***	0.229***
	(10.52)	(10.65)
$Age_{i,t}$	0.017	0.022
	(0.25)	(0.31)
$Frs_{i,t}$	0.543***	0.535***
	(4.89)	(4.76)
Constant	2.994***	2.931***
	(8.25)	(8.10)
Observations	8,632	8,632
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Adjusted R^2	0.535	0.530

where $UE_{i,j}$ are the emissions of industrial major pollutants per unit output value, $\min(UE_j)$ and $\max(UE_j)$ are the minimum and maximum values of major pollutants in all industries, respectively, and $UE^s_{i,j}$ is the standardized value.

Third, we sum up the emissions of four pollutants per unit output value $UE^s_{i,j}$ to obtain the industrial pollution intensity γ_i:

$$\gamma_i = \sum_{j=1}^{n} UE^s_{i,j} \tag{5}$$

Fourth, we classify the industrial sectors based on the median emission intensity of industrial pollution. The industries with $\gamma_i > 0.1669$ are heavily polluting industries, and other industries are non-heavily polluting industries.

The regression results obtained from changing the treatment group and the control group are reported in Table 10. The coefficient of $Treat_i * Post_t$ is 0.078 (t value = 2.75) in Column (1), which is statistically significant at the 1% level.

5.6.2. Alternative dependent variable

To eliminate the influence of the deviation of index calculation, we employ TFP measured using the OP method as a substitute index. The coefficient of $Treat_i * Post_t$ is still clearly positive at the 1% significance level in Column (2), further confirming *Hypothesis 1* that the green credit policy significantly improves corporate total factor productivity.

Table 10

Robustness check: Change indicator Table 10 presents the results of changing indicator. First, we redefine the heavily polluting firms and the result is shown in Column (1). Then we use the alternative measurement of TFP, namely $OPTFP_{i,t}$, which is calculated by OP method. The result is shown in Column (2).

Dependent variables	$TFP_{i,t}$ (1)	$OPTFP_{i,t}$ (2)
$Treat_i * Post_t$	0.078***	0.074***
	(2.75)	(2.91)
$Post_t$	-0.126***	-0.123***
	(-3.24)	(-3.23)
$Treat_i$	0.011	-0.049
	(0.26)	(-1.28)
$Size_{i,t}$	0.172***	0.206***
	(10.89)	(13.19)
$Lev_{i,t}$	0.667***	0.663***
	(6.42)	(6.45)
$Roa_{i,t}$	2.366***	2.424***
	(9.65)	(10.00)
$Fixs_{i,t}$	-2.517***	-2.347***
	(-20.88)	(-19.67)
$Growth_{i,t}$	0.144***	0.142***
	(8.48)	(8.49)
$Klratio_{i,t}$	0.227***	0.210***
	(10.59)	(10.02)
$Age_{i,t}$	0.017	0.017
	(0.24)	(0.24)
$Frs_{i,t}$	0.542***	0.538***
	(4.82)	(4.87)
Constant	2.932***	2.786***
	(8.07)	(7.77)
Observations	8,632	8,632
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Adjusted R^2	0.530	0.537

5.7. Control macroeconomic determinants

To eliminate the potential impact of macroeconomic factors on our results, following Gulen and Ion (2016), in Eq. (2), we add the annual year-on-year growth rate of the regional GDP ($\triangle GPD_t$), the natural logarithm of the regional per capita GDP ($LnGDP_t$), the regional unemployment rate ($Unemployment_t$), and the annual year-on-year growth rate of regional fixed asset investment ($TFAIG_t$) to control for the potential impact of macroeconomic factors.

Table 11 reports the results after controlling for the macroeconomic factors. The coefficient of $Treat_i * Post_t$ is still significantly positive at the 5% significance level, indicating that our results are robust.

5.8. Multiple fixed-effect models

Potential problems may arise due to the neglect of other factors, such as time-varying policies among firms, industries, and provinces. To mitigate these problems, following Liu (2016) and Yuan et al. (2016), we conduct multiple fixed-effect models to re-estimate Eq. (2).

The results are presented in Table 12: the results in Column (1) control for the firm fixed effects and year fixed effects; the results in Column (2) control for the firm fixed effects with the industry-year fixed effects; the results in Column (3) control for the firm fixed effects with the province-year fixed effects; and the results in Column (4) control for the firm fixed effects with the industry-year fixed effects and the province-year fixed effects. The coefficients of $Treat_i * Post_t$ are significantly positive at least at the 5% significance level, showing that the positive effect of the green credit policy on TFP is not driven by the firm characteristics, the time-varying industry, or the time-varying province.

Table 11
Robustness check: Control macroeconomics determinants Table 11 reports the result when macroeconomic factors are added. $\triangle GPD_t$ is the annual year-on-year growth rate of regional GDP, $LnGDP_t$ is the natural logarithm of regional per capita GDP, $Unemployment_t$ is the regional unemployment rate, and $TFAIG_t$ is the annual year-on-year growth rate of regional fixed asset investment.

Dependent variable	$TFP_{i,t}$
$Treat_i$ * $Post_t$	0.053**
	(2.08)
$Post_t$	-0.247***
	(-4.24)
$Treat_i$	-0.029
	(-0.73)
$Size_{i,t}$	0.167***
	(10.31)
$Lev_{i,t}$	0.709***
	(6.73)
$Roa_{i,t}$	2.422***
	(9.82)
$Fixs_{i,t}$	-2.385***
	(-19.88)
$Growth_{i,t}$	0.142***
	(8.27)
$Klratio_{i,t}$	0.216***
	(9.96)
$Age_{i,t}$	-0.012
	(-0.17)
$Frs_{i,t}$	0.510***
	(4.62)
$\triangle GPD_t$	-0.231
	(-0.65)
$LnGDP_t$	0.190***
	(4.36)
$Unemployment_t$	6.142**
	(2.55)
$TFAIG_t$	-0.229*
	(-1.85)
Constant	1.139**
	(1.98)
Observations	8,411
Industry Fixed Effects	Yes
Year Fixed Effects	Yes
Adjusted R^2	0.544

6. Additional analysis

In this section, we further examine the heterogeneous impact of firm characteristics, external monitoring mechanisms, and regional differences on the relationship between the green credit policy and TFP.

6.1. Firm characteristics

There is no universal policy, and heterogeneity analysis allows us to observe the response of different types of firms to policy shocks. Different types of firms differ in their handling of risks, resource allocation, and response to policy shocks (Hu et al., 2021), and thus the ability of firms with different firm characteristics to respond to bank loan shocks from the green credit policy varies. The analysis of firm characteristics in this paper focuses on the nature of ownership and firm size.

Chinese firms have unique ownership characteristics, with the ultimate control of many firms vested in the state. Yao et al. (2021) pointed out that SOEs have more political tasks and non-market functions than non-SOEs, so it easier for them to obtain additional government support. Because the government is prone to favor SOEs, they generally have soft environmental constraints, causing them to face a lower cost of environmental violations. In addition, the banking system, dominated by state-owned banks, makes banks engage in less oversight of SOEs (Firth et al., 2008), and it is easier for SOEs to obtain bank loans. Thus, in the face of green credit policy shocks, non-SOEs face stronger survival pressure than SOEs. Following Chakraborty and Chatterjee (2017), we

Table 12
Robustness checks: Multiple fixed effect models Table 12 reports the regression results of multiple fixed effects. Column (1), (2), (3), (4) report the results of firm fixed effects and firm fixed effects, firm fixed effects with industry-year fixed effects, firm fixed effect with province-year fixed effects, and firm fixed effect with industry-year fixed effect and province-year fixed effect, respectively.

Dependent variable	$TFP_{i,t}$ (1)	$TFP_{i,t}$ (2)	$TFP_{i,t}$ (3)	$TFP_{i,t}$ (4)
$Treat_i$ * $Post_t$	0.054***	0.093***	0.037**	0.067***
	(3.59)	(5.31)	(2.34)	(3.68)
$Size_{i,t}$	0.154***	0.145***	0.138***	0.126***
	(13.46)	(12.37)	(11.81)	(10.51)
$Lev_{i,t}$	0.173***	0.144***	0.155***	0.120***
	(3.87)	(3.20)	(3.40)	(2.62)
$Roa_{i,t}$	1.947***	1.952***	1.986***	1.982***
	(19.07)	(18.88)	(18.85)	(18.54)
$Fixs_{i,t}$	-2.140***	-2.096***	-2.164***	-2.116***
	(-36.97)	(-35.77)	(-36.90)	(-35.62)
$Growth_{i,t}$	0.177***	0.180***	0.168***	0.172***
	(22.34)	(22.50)	(20.78)	(21.01)
$Klratio_{i,t}$	0.189***	0.188***	0.200***	0.200***
	(22.28)	(21.86)	(23.12)	(22.70)
$Age_{i,t}$	0.012	-0.015	-0.003	-0.010
	(0.13)	(-0.15)	(-0.03)	(-0.09)
$Frs_{i,t}$	0.140*	0.122	0.074	0.063
	(1.91)	(1.64)	(0.98)	(0.83)
Constant	4.396***	4.569***	4.673***	4.878***
	(13.10)	(12.75)	(13.03)	(12.88)
Observations	8,632	8,632	8,632	8,632
Year Fixed Effects	Yes	No	No	No
Firm Fixed Effects	Yes	Yes	Yes	Yes
Industry*Year Fixed Effects	No	Yes	No	Yes
Province*Year Fixed Effects	No	No	Yes	Yes
Adjusted R^2	0.344	0.366	0.369	0.391

Table 13
Additional analysis: Firm characteristics Table 13 reports the results of heterogeneity analysis based on firm characteristics. We classify firms into SOEs group and Non-SOEs group according to their ultimate controllers, the results are shown in Columns (1) and (2). Then, we classify firms into large-scale firms and small-scale firms based on the median size of firms in the same industry in the same year, the results are shown in Columns (3) and (4).

	Firms' state ultimate controller		Firm size	
Dependent variable ($TFP_{i,t}$)	Non-SOEs (1)	SOEs (2)	Small-scale (3)	Large-scale (4)
$Treat_i$ * $Post_t$	0.101**	0.037	0.082**	0.041
	(2.11)	(1.33)	(2.27)	(1.25)
$Post_t$	-0.252***	-0.027	-0.111**	-0.069
	(-3.99)	(-0.52)	(-2.00)	(-1.18)
$Treat_i$	-0.055	-0.141***	-0.067	-0.107*
	(-0.86)	(-2.62)	(-1.26)	(-1.68)
$Size_{i,t}$	0.198***	0.135***	0.198***	0.110***
	(6.66)	(5.87)	(5.74)	(4.09)
$Lev_{i,t}$	0.246*	0.153	0.254***	0.157
	(1.88)	(1.62)	(2.72)	(1.40)
$Roa_{i,t}$	1.880***	2.012***	1.854***	2.126***
	(6.68)	(10.29)	(9.67)	(8.13)
$Fixs_{i,t}$	-2.714***	-1.996***	-2.170***	-2.266***
	(-14.28)	(-15.90)	(-15.17)	(-14.35)
$Growth_{i,t}$	0.192***	0.167***	0.188***	0.163***
	(9.02)	(9.54)	(9.70)	(8.39)
$Klratio_{i,t}$	0.191***	0.212***	0.142***	0.262***
	(4.09)	(7.29)	(3.86)	(6.94)
$Age_{i,t}$	0.107	0.036	0.057	0.047
	(1.02)	(0.40)	(0.66)	(0.48)
$Frs_{i,t}$	0.136	0.316**	0.444**	0.134
	(0.55)	(2.28)	(2.29)	(0.87)
Constant	3.110***	4.319***	3.597***	4.230***
	(4.55)	(7.66)	(4.79)	(5.61)
Observations	2,971	5,661	4,351	4,281
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.391	0.349	0.359	0.343

classify firms into an SOE group and a non-SOE group according to their ultimate controllers, and Columns (1) and (2) of Table 13 report the policy effects for the non-SOE group and the SOE group, respectively. We find that the coefficient of $Treat_i * Post_t$ is significantly positive at the 5% significance level in the non-SOE group, while it is positive but insignificant in the SOE group. The results indicate that non-SOEs are more sensitive to the green credit policy due to survival pressure.

In addition, we explore whether there is heterogeneity in policy effects across firm sizes. Large firms typically have a higher reputation and social credit, and they have more mortgaged assets and sufficient liquid assets (Petersen and Rajan, 1997). Therefore, when faced with enhanced bank loan financing constraints brought about by the green credit policy, large firms can supplement their working capital through commercial credit and cash on hand to alleviate the financing constraints. However, small-scale firms face more stringent policy pressure and greater survival pressure due to limited financing channels. Following Cai et al. (2020) and Tang et al. (2020), we classify firms into large-scale firms and small-scale firms based on the median size of firms in the same industry in the same year to explore whether firms of different sizes are affected differently by the policy. Columns (3) and (4) of Table 13 report the results for small-scale firms and large-scale firms, respectively. We can see that the coefficient of $Treat_i * Post_t$ is significantly positive at the 5% significance level in the small-scale firms, which is consistent with our *Hypothesis 2a*.

6.2. External monitoring mechanisms

With the implementation of the Guidelines in 2012, the China Banking Regulatory Commission (CBRC) put forward further requirements for all kinds of banks, obliging them to intensify the examination of loan firms and implement the risk exposure management system. Therefore, the green credit policy further emphasizes the supervisory role of banks in the process of corporate governance. Compared with firms with stronger external monitoring, the Guidelines give banks a greater incentive to play the supervisory role in firms with weaker external monitoring, thereby improving the TFP of those firms. Therefore, we posit that the Guidelines have prominent effects on TFP in firms with weak external supervision.

We use the following three indicators to measure the external monitoring level: Big 4 auditors, institutional investor shareholding, and analyst coverage. Following Yuan et al. (2016), we classify the full sample into two groups according to the above three indicators. The first group is the weaker external monitoring group, including firms with non-Big 4 auditors, low institutional ownership, and low analyst coverage. The second group is the stronger external monitoring group, consisting of firms with Big 4 auditors, high institutional ownership, and high analyst coverage. Table 14 presents the results according to the external monitoring level. The coefficients of $Treat_i * Post_t$ in the group with weaker external monitoring are all significantly positive at the 1% level, while the coefficients of $Treat_i * Post_t$ in the group with stronger external monitoring are all insignificant, supporting *Hypothesis 2b*. The results indicate that the Guidelines only have an impact on the firms with weaker external monitoring, further verifying the external monitoring role of banks.

6.3. Regional differences

Hao et al. (2010) pointed out that the complete and systematic regional environment is beneficial to the flow of innovation resources and the improvement of investment opportunities. It can also support firms in their efforts to improve their resource allocation efficiency. Eastern China has a more developed economy, with many production subjects, more professional talents, and high investment opportunity efficiency than the central and western regions; therefore, the green

Table 14
Additional analysis: External monitoring mechanisms Table 14 reports the results of heterogeneity analysis based on external monitoring mechanisms. We classify the full sample into two groups: the first group is the weaker external monitoring group, including firms with non-Big 4 auditors, low institutional ownership, and low analyst coverage; the second group is the stronger external monitoring group, including firms with Big 4 auditors, high institutional ownership, and high analyst coverage. Based on the median of institutional investor shareholding (analyst coverage) in the same industry in the same year, the firm is divided into High/Low institutional ownership (High analyst/low analyst).

	Weaker monitoring mechanisms			Stronger monitoring mechanisms		
Dependent variable ($TFP_{i,t}$)	Non Big4	Low Analyst	Low Institutional Ownership	Big4	High Analyst	High Institutional Ownership
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat_i * Post_t$	0.073***	0.156***	0.173***	0.130	0.021	-0.018
	(2.69)	(3.30)	(4.07)	(1.35)	(0.64)	(-0.51)
$Post_t$	-0.093**	-0.187***	-0.117**	-0.301**	-0.077	-0.148**
	(-2.31)	(-3.25)	(-2.16)	(-2.28)	(-1.62)	(-2.58)
$Treat_i$	-0.059	-0.057	-0.120**	0.038	-0.041	0.009
	(-1.48)	(-1.18)	(-2.33)	(0.25)	(-0.91)	(0.18)
$Size_{i,t}$	0.153***	0.142***	0.195***	0.215***	0.178***	0.158***
	(8.47)	(5.80)	(8.16)	(4.36)	(10.84)	(8.57)
$Lev_{i,t}$	0.728***	0.713***	0.568***	0.262	0.663***	0.773***
	(6.74)	(5.62)	(4.08)	(0.71)	(5.54)	(5.41)
$Roa_{i,t}$	2.490***	2.326***	1.982***	1.014	2.370***	2.835***
	(9.95)	(6.77)	(6.72)	(1.06)	(8.12)	(7.42)
$Fixs_{i,t}$	-2.500***	-2.514***	-2.614***	-2.306***	-2.474***	-2.326***
	(-19.10)	(-18.00)	(-16.31)	(-7.65)	(-17.48)	(-14.66)
$Growth_{i,t}$	0.141***	0.151***	0.211***	0.181**	0.133***	0.102***
	(8.13)	(6.61)	(6.44)	(2.50)	(4.96)	(5.12)
$Klratio_{i,t}$	0.230***	0.244***	0.218***	0.209***	0.220***	0.244***
	(10.00)	(9.54)	(7.77)	(3.37)	(9.10)	(9.31)
$Age_{i,t}$	0.012	0.094	-0.055	0.213	-0.013	0.118
	(0.16)	(1.09)	(-0.59)	(0.93)	(-0.17)	(1.37)
$Frs_{i,t}$	0.555***	0.562***	0.536***	0.495	0.554***	0.595***
	(4.73)	(4.02)	(2.78)	(1.26)	(4.62)	(4.11)
Constant	3.279***	3.234***	2.839***	1.041	2.902***	2.635***
	(8.29)	(6.55)	(5.18)	(0.79)	(7.28)	(5.97)
Observations	7,947	3,499	4,344	685	5,133	4,288
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.521	0.531	0.504	0.562	0.528	0.542

Table 15
Additional analysis: Regional differences Table 15 reports the results of heterogeneity analysis based on different regions. Based on registered firm address, the full sample is divided to Eastern China, mid China, and Western China. The results are shown in Column (1), (2), and (3), respectively.

Dependent variable ($TFP_{i,t}$)	Eastern China $TFP_{i,t}$ (1)	Mid-China $TFP_{i,t}$ (2)	Western China $TFP_{i,t}$ (3)
$Treat_i * Post_t$	0.078**	0.047	0.023
	(2.39)	(0.82)	(0.37)
$Post_t$	-0.167***	-0.059	0.058
	(-3.57)	(-0.66)	(0.56)
$Treat_i$	-0.006	-0.056	0.002
	(-0.12)	(-0.67)	(0.02)
$Size_{i,t}$	0.183***	0.141***	0.135***
	(8.75)	(4.12)	(3.88)
$Lev_{i,t}$	0.775***	0.437*	0.629***
	(5.60)	(1.93)	(3.32)
$Roa_{i,t}$	2.201***	2.805***	2.292***
	(6.30)	(6.07)	(4.59)
$Fixs_{i,t}$	-2.744***	-2.108***	-1.991***
	(-17.18)	(-8.63)	(-7.11)
$Growth_{i,t}$	0.140***	0.111***	0.169***
	(5.93)	(2.82)	(4.97)
$Klratio_{i,t}$	0.219***	0.314***	0.192***
	(8.03)	(7.17)	(3.63)
$Age_{i,t}$	0.087	-0.102	-0.135
	(1.03)	(-0.63)	(-0.83)
$Frs_{i,t}$	0.456***	0.728***	0.620***
	(3.02)	(3.48)	(2.69)
Constant	2.731***	2.884***	4.079***
	(5.80)	(3.57)	(5.09)
Observations	5,288	1,632	1,496
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Adjusted R^2	0.544	0.502	0.518

credit policy may be more effective in promoting the total factor productivity improvement of heavily polluting firms in the developed eastern region.

In this section, we explore whether the relationship between the green credit policy and TFP varies in different regions. Registered public firms are divided into three groups according to their place of incorporation, namely Eastern China, Central China, and Western China. Table 15 presents the impact of the green credit policy on the TFP in different regions. The coefficient of $Treat_i * Post_t$ is 0.078 and is significant at the 5% level in Column (1). However, the coefficients of $Treat_i * Post_t$ are insignificant in Columns (2) and (3), supporting *Hypothesis 2c*. The results indicate that the green credit policy improves the TFP of heavily polluting firms in the developed eastern region, which is

$$R\&D_{i,t} = \alpha_0 + \alpha_1 Treat_i * Post_t + \alpha_2 Post_t + \alpha_3 Treat_i + \sum_k \gamma_k Control_{k,i,t} + \sum Industry + \sum Year + \varepsilon_{i,t} \quad (6)$$

consistent with Li (2010).

7. Channel analysis

We discuss the economic mechanisms of the green credit policy affecting corporate total factor productivity in this section. Lian (2012) pointed out that TFP is the "surplus" in output growth and cannot be explained by factor inputs, reflecting the efficiency of transforming inputs into outputs. It results not from increasing inputs but from technological advances, efficiency improvements, scale economy, and so on. We explore the economic mechanisms through which the green credit policy improves corporate total factor productivity by affecting technological innovation and resource allocation efficiency.

7.1. Effect of technological innovation

To investigate whether the green credit policy promotes total factor productivity through technological innovation, following Dangelico (2016) and Bu et al. (2020), we adopt corporate R&D investment as a proxy for technological innovation to test the economic mechanism. Specifically, following Kim and Zhang (2016), we implement the two-step regression method. First, we check the connection between green credit and corporate innovation. Second, we check the relationship between technological innovation and corporate TFP. The specific regression model is as follows:

$$TFP_{i,t} = \beta_0 + \beta_1 R\&D_{i,t} + \sum_k \gamma_k Control_{k,i,t} + \sum Industry + \sum Year + \varepsilon_{i,t} \quad (7)$$

where $R\&D_{i,t}$ is the proxy for corporate innovation, calculated as R&D investment divided by sales; the other variables are consistent with Eq. (2).

Table 16 presents the regression results. Panel A provides the results of Eq. (6); the regression coefficient of $Treat_i * Post_t$ is 0.007 (t value = 3.29), which is significant at the 1% level, indicating that the Guidelines

Table 16
Channel test: The impact of technology innovation Table 16 reports the two-stage channel analysis of technology innovation. Panel A shows the impact of $Treat_i * Post_t$ on technology innovation. Panel B reports the impact of technology innovation on corporate total factor productivity.

Panel A:		Panel B:	
Dependent variable	$R\&D_{i,t}$	Dependent variable	$TFP_{i,t}$
$Treat_i * Post_t$	0.007***	$R\&D_{i,t}$	1.061***
	(3.29)		(6.68)
$Post_t$	0.032***	$Size_{i,t}$	0.171***
	(10.42)		(25.68)
$Treat_i$	-0.006***	$Lev_{i,t}$	0.647***
	(-4.51)		(14.77)
$Size_{i,t}$	-0.001	$Roa_{i,t}$	2.376***
	(-1.48)		(16.78)
$Lev_{i,t}$	-0.016***	$Fixs_{i,t}$	-2.498***
	(-4.35)		(-48.06)
$Roa_{i,t}$	0.009	$Growth_{i,t}$	0.143***
	(0.52)		(10.48)
$Fixs_{i,t}$	-0.006*	$Klratio_{i,t}$	0.230***
	(-1.82)		(28.11)
$Growth_{i,t}$	0.000	$Age_{i,t}$	0.004
	(0.01)		(0.15)
$Klratio_{i,t}$	0.001	$Frs_{i,t}$	0.534***
	(0.84)		(11.24)
$Age_{i,t}$	-0.016***		
	(-6.34)		
$Frs_{i,t}$	-0.010**		
	(-2.45)		
Constant	0.057***	Constant	2.939***
	(3.63)		(18.12)
Observations	8,632	Observations	8,632
Industry Fixed Effects	Yes	Industry Fixed Effects	Yes
Year Fixed Effects	Yes	Year Fixed Effects	Yes
Adjusted R^2	0.119	Adjusted R^2	0.532

Table 17
Channel test: The impact of resource allocation efficiency Table 17 reports the two-stage channel analysis of allocation efficiency. Panel A shows the effect of $Treat_i * Post_t$ on resource allocation efficiency. Panel B shows the impact of resource allocation efficiency on corporate total factor productivity.

Panel A: Dependent variable	$\text{Efficiency}_{i,t}$	Panel B: Dependent variable	$\text{TFP}_{i,t}$
$Treat_i * Post_t$	-0.004**	$Efficiency_{i,t}$	-1.462***
	(-2.36)		(-5.26)
$Post_t$	-0.003***	$Size_{i,t}$	0.169***
	(-2.63)		(10.58)
$Treat_i$	0.003***	$Lev_{i,t}$	0.666***
	(2.82)		(6.33)
$Size_{i,t}$	-0.002***	$Roa_{i,t}$	2.396***
	(-5.73)		(9.69)
$Lev_{i,t}$	0.012***	$Fixs_{i,t}$	-2.476***
	(4.94)		(-20.83)
$Roa_{i,t}$	0.022***	$Growth_{i,t}$	0.145***
	(2.82)		(8.37)
$Fixs_{i,t}$	0.004	$Klratio_{i,t}$	0.235***
	(1.23)		(10.96)
$Growth_{i,t}$	0.000	$Age_{i,t}$	0.002
	(0.04)		(0.03)
$Klratio_{i,t}$	0.004***	$Frs_{i,t}$	0.536***
	(8.58)		(4.74)
$Age_{i,t}$	-0.009***		
	(-6.19)		
$Frs_{i,t}$	-0.006**		
	(-2.52)		
Constant	0.052***	Constant	2.987***
	(5.96)		(8.22)
Observations	8,632	Observations	8,632
Industry Fixed Effects	Yes	Industry Fixed Effects	Yes
Year Fixed Effects	Yes	Year Fixed Effects	Yes
Adjusted R^2	0.063	Adjusted R2	0.531

have significantly promoted technological innovation. Panel B contains the results of Eq. (7); the regression coefficient of $R\&D_{i,t}$ is 1.061 (t value = 6.68), which is also significant at the 1% level. This verifies the neoclassical economic growth theory that technological innovation promotes the improvement of corporate TFP. The above results confirm that the green credit policy enhances TFP by promoting corporate technological innovation.

7.2. Effect of resource allocation efficiency

Resource allocation efficiency refers to the benefit generated by the distribution of input factors in each output subject under a certain technical level. The measurement of resource allocation efficiency consists of two levels, namely the macro level and the micro level. This paper mainly explores whether the green credit policy further promotes total factor productivity by affecting the resource allocation efficiency of micro firms.

There are two main approaches in the existing literature to measure the resource allocation efficiency of firms. One is to measure the resource allocation efficiency from the perspective of their ability to seize investment opportunities (McLean et al., 2012; Bhandari and Javakhadze, 2017; Xu, 2018),[14] and the other is to measure resource allocation efficiency from the perspective of investment efficiency[15] (Xu and Zhang, 2009; Tang and Lin, 2014).

At the current stage of China's economic transformation, the optimization of resource allocation efficiency is an important goal of supply-side structural reform. Cai and Ye (2020c) pointed out that whether a firm's investment level matches its investment opportunity is an important indicator to measure its resource allocation efficiency. Therefore, to reflect further the mediating effect of resource allocation efficiency, we measure the resource allocation efficiency from the perspective of investment efficiency. If the implementation of the green credit policy can improve the investment efficiency of firms, it indicates that the resource utilization rate in heavily polluting firms is significantly enhanced. The improved resource utilization rate promotes the improvement of total factor productivity, which further reflects the policy effect.

The matching degree between the actual capital investment level and the investment opportunity is an important index reflecting corporate investment efficiency (Gomariz et al., 2014; Tang and Lin, 2014). Therefore, using the model proposed by Richardson (2006), we first estimate firms' normal capital investment level, and then we use the absolute value of the difference between the actual capital investment level and the estimated normal investment level to measure the corporate resource allocation efficiency. The specific model is as follows:

$$Invest_{i,t} = \alpha_0 + \alpha_1 Invest_{i,t-1} + \alpha_2 Size_{i,t-1} + \alpha_3 Lev_{i,t-1} + \alpha_4 Age_{i,t-1} + \alpha_5 Cashhold_{i,t-1} + \alpha_6 Return_{i,t-1} + \alpha_7 Growth_{i,t-1} + \sum Industry + \sum Year + \varepsilon_{i,t} \quad (8)$$

[14] Based on the investment–investment opportunity sensitivity model to measure the resource allocation efficiency of firms.

[15] Investment efficiency reflects whether a firm makes full use of the relevant resources for value creation, which is of great significance to corporate development and macroeconomic performance.

where $Invest_{i,t}$ is the proxy for firms' investment level; $Cashhold_{i,t-1}$ is the proxy for firms' cash holding; $Return_{i,t-1}$ represents the market-adjusted stock return; and the other variables are consistent with Eq. (2). The absolute value of the residual is the proxy variable of firms' capital allocation efficiency, which is expressed by $Efficiency_{i,t}$, and the higher the index is, the lower the resource allocation efficiency is.

Consistent with the above, we use the two-step regression method to explore whether the green credit policy affects TFP by improving the resource allocation efficiency. The specific model is as follows:

$$Efficiency_{i,t} = \alpha_0 + \alpha_1 Treat_i * Post_t + \alpha_2 Post_t + \alpha_3 Treat_i + \sum_k \gamma_k Control_{k,i,t} + \sum Industry + \sum Year + \varepsilon_{i,t} \tag{9}$$

$$TFP_{i,t} = \beta_0 + \beta_1 Efficiency_{i,t} + \sum_k \gamma_k Control_{k,i,t} + \sum Industry + \sum Year + \varepsilon_{i,t} \tag{10}$$

where $Efficiency_{i,t}$ is the measure index of corporate resource allocation efficiency. The higher the index is, the lower the resource allocation efficiency is.

Table 17 presents the regression results. Panel A contains the results of Eq. (9); the regression coefficient of $Treat_i * Post_t$ is -0.004 (t value = -2.36), which is significantly negative at the 5% significance level. Panel B presents the results of Eq. (10), and the coefficient of $Efficiency_{i,t}$ is significant and negative at the 1% significance level. The results reflect that the implementation of the credit policy makes treatment firms improve their resource allocation efficiency significantly, revealing that green credit exerts an influence on firms' TFP by improving their resource allocation efficiency.

8. Conclusion

In 2012, China issued the "Green Credit Guidelines," which clearly make green development responsibility of banks in the process of granting credit. Based on this exogenous event, this study investigates the effect of green credit on the total factor productivity of heavily polluting firms. The baseline result indicates that the green credit policy improves the total factor productivity of heavily polluting firms. This result is still valid after a series of robustness tests, including the effectiveness test of the green credit policy, parallel trend test, placebo test, PSM-DID test, excluding the impact of other contemporary policies, replacing indicators, and controlling for the impact of macroeconomic factors. Further analysis indicates that the effect of the green credit policy on TFP is prominent for non-SOEs, small-scale firms, firms with weak external monitoring, and firms in eastern China. The results of the channel analysis show that the green credit policy mainly affects corporate total factor productivity by promoting corporate innovation and improving resource allocation efficiency.

The empirical results of this paper have the following three policy implications. First, this paper affirms the positive role of the green credit policy and shows that it can improve corporate governance, improve corporate innovation and resource allocation efficiency, and realize a win-win situation between environmental development and economic growth efficiency. Therefore, with the milestones achieved in the green credit policy, the government should take the initiative to continue to improve it, increase the investment in green financial facilities, strengthen the environmental risk awareness of financial institutions and firms, and guide and urge financial institutions and firms to practice the green principle rigorously.

Second, this paper extends the research on total factor productivity to the micro level and finds that technological innovation and resource allocation efficiency are the main channels through which heavily polluting firms can improve their total factor productivity. Therefore, the government should encourage firms to invest in technological innovation and fully mobilize employees' enthusiasm and creativity to improve their productivity.

Third, the findings of this paper show that there is no contradiction between environmental regulation and the high-quality development of the real economy. The key lies in adopting appropriate policies and means. However, this study also finds that the green credit policy has heterogeneity in different firm characteristics, the corporate governance environment, and the regional development degree, confirming that "it is difficult for market mechanism to give consideration to fairness in the pursuit of benefits." Therefore, in the supervision of environmental issues, the government cannot apply a one-size-fits-all strategy; it should carry out timely revisions and adjustments to relevant policies according to the development of regions and firms. At the same time, the government needs to focus on and strengthen the policy implementation in areas with a lower marketization level to enable the policy to play a full role in these areas.

Like the previous literature, this paper has some limitations, which provide directions and suggestions for future research. First, the pursuit of environmental performance (the reduction of energy consumption and environmental pollutant emissions) and the improvement of economic performance are the significant differences between the green credit policy and the traditional credit policy. This paper finds that the green credit policy significantly promotes the improvement of the total factor productivity of heavily polluting firms, which mainly focus on the economic performance of the green credit policy. This paper does not carefully analyze the impact of the green credit policy on the specific environmental performance of heavily polluting firms. Therefore, relevant research can further explore whether the green credit policy can inhibit the emission of pollutants and promote the upgrading of green product technology. Second, green credit brings environmental risks into credit management, provides credit support for environment-friendly firms, and strictly prevents credit funds from flowing into polluting firms. Starting with the punishment effect of green credit, this paper explores the impact of the green credit policy on heavily polluting firms but lacks an analysis of the supporting effect of the green credit policy. Therefore, with the availability of future data, we can further explore whether green firms are positively affected by green credit and determine what kind of impact the green credit policy has on green firms' decision making and performance. Finally, this paper only focuses on the impact of the green credit policy in the environmental regulation policy. There are some other environmental regulation policies that can be considered, such as the environmental protection law, carbon emission rights, water rights, and so on.

Declaration of Competing Interest

We have no conflict of interest to declare.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.techfore.2022.121516.

Appendix. Definitions of variables

Variables	Definitions
$TFP_{i,t}$	The value of corporate TFP, see Eq. (1) for the specific algorithm.
$OPTFP_{i,t}$	The alternative measurement of corporate TFP, which is calculated by OP method.
$Treat_i$	A binary variable, which equals to 1 if firm *i* belongs to heavily polluting firm, and 0 otherwise.
$Post_t$	A year dummy variable that equals to 1 if the observation year is from 2012 to 2015, and 0 if the observation year is from 2008 to 2011
$Size_{i,t}$	Natural logarithm of total assets.
$Lev_{i,t}$	The asset-liability ratio of the firm.
$Roa_{i,t}$	The return on assets of the firm.
$Fixs_{i,t}$	The proportion of fixed assets, which equals to the fixed assets divided by the assets.
$Growth_{i,t}$	The sales growth rate.
$Klratio_{i,t}$	Capital labor ratio, which equals to the average annual net fixed assets balance divided by the number of employees.
$Age_{i,t}$	Natural logarithm of the firm listed age.
$Frs_{i,t}$	The number of shares held by top1 shareholder divided by total shares.
$SOE_{i,t}$	A binary variable, which equals to 1 if the firm belongs to state-owned enterprise, and 0 otherwise.
$Big4_{i,t}$	A binary variable, which equals to 1 if the auditor of the firm comes from the four international accounting firms, and 0 otherwise.
$Analyst_{i,t}$	Analyst coverage, which equals to the natural logarithm of analyst number plus 1.
$Institutional\ Ownership_{i,t}$	The percentage of institutional investor shareholding.
$R\&D_{i,t}$	The R&D expense divided by sales and the missing values of R&D are replaced by 0.
$Cashhold_{i,t}$	The cash holding and cash equivalent holding of the firm divided by total assets.
$Efficiency_{i,t}$	Resource allocation efficiency, which equals to the absolute value of the residuals in Eq. (8).

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