Make every dollar count: The impact of green credit regulation on corporate green investment efficiency

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A B S T R A C T
This paper systematically examines the impact of green credit regulation on the efficiency of corporate green investment. The results show that green credit policy significantly decreases green investment efficiency for heavily polluting firms. This is further evidenced through the fact that these firms are more inclined to make symbolic efforts to pursue more credit resources rather than engaging in substantive green investments to drive real green transition. This negative effect is more pronounced for small, non-state-owned and non-foreign-funded firms. Our further analysis suggests that the intensity of environmental law enforcement, the level of financial development, and intellectual property protection can mitigate this negative effect of green credit policy on green investment efficiency. Our study is groundbreaking in that it makes the first attempt to calculate the future value that green investment can create, which serves the basis for analyzing the economic effects of green investment at the industry level. The findings indicate that labor-intensive industries with close ties to consumers' daily lives have a higher future value for green investment. Conversely, capital-intensive industries such as the metallurgical industry have a lower future value for green investment. These findings emphasize the need to improve green credit regulation and make genuine green investment to accelerate real green transition in emerging economies.

1. Introduction

Environmental degradation and resource constraints have emerged as pressing global concerns, prompting the United Nations to advocate for green development to tackle these challenges (He et al., 2022). Firms, as the primary resource consumers and major contributors to environmental problems (He et al., 2022; Li et al., 2023; Liu et al., 2023), play a crucial role in addressing pollution through effective environmental measures. However, green transition requires substantial investments (Liu et al., 2022a; Tian et al., 2022; Wu et al., 2024). On one hand, such investments may impact a firm's financial performance by competing for resources and introducing revenue uncertainty. On the other hand, they offer the advantages of reducing emissions and improving the quality of the natural environment (Chen and Ma, 2021). Hence, how to guide firms towards prudent green investments is of vital importance for the effectiveness of environmental improvement (Yang et al., 2023). Recognizing the environmental challenges, governments worldwide have implemented reforms that integrate economic growth with environmental protection (Lee et al., 2022a), with green finance regulations playing a vital role. Green credit regulations are regarded as valuable financial tools that help balance the economy and the environment (Chen et al., 2021b; Hussain et al., 2022; Wen et al., 2021). For instance, China's “Green Credit Guidelines” issued by the China Banking Regulatory Commission (CBRC) in 2012 provide a normative framework for green credit (Yao et al., 2021a). These guidelines urge banks to reduce loans to high-energy-consuming and heavily polluting firms while increasing loans to low-polluting and clean projects.

However, there is an imbalance in the distribution of credit resources among industries, which contributes to environmental degradation (Lee et al., 2022a). For example, among the top 10 industries in China receiving the highest green credits, six belong to heavily polluting sectors1 (Zhang et al., 2022a). Hsieh and Klenow (2009) find that the

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1 The data is sourced from the China Industrial Enterprise Database.
United States and India also prefer allocating financial resources to large polluting industries. Theoretically, green credit can mitigate environmental degradation by influencing credit allocation and corporate decisions such as technological innovation and green investments. The pressure of green credit leads to stricter regulations for firms (Lv et al., 2021). To avoid environmental penalties, firms need to increase their investment in environmental governance and improve the investment efficiency (Liang and Liu, 2017). However, the impact of green credit on improving green investment efficiency depends on external factors such as the effectiveness of green credit policy implementation and the strategies adopted by firms in response to such policies (Zhang et al., 2022a). Kesidou and Demirel (2012) reveal that while green credit regulation increases firms’ green investments, many of these investments are often motivated by “greenwashing.”

Greenwashing refers to firms portraying themselves as environmentally friendly to conceal their negative environmental impact and enhance their market presence or influence (Wu et al., 2021). For example, firms may selectively report environmental-protection efforts or exaggerate green investments (Zhang, 2022). It enables firms to create a positive green image, avoid regulatory penalties, and attract financial support, thereby reducing their financing costs (Zhang, 2022). Consequently, regulatory supervision of the green financial system inadvertently encourages the greenwashing behavior of heavily polluting firms (Zhang et al., 2020). Therefore, these firms tend to focus more on symbolic green investments, potentially compromising the actual efficiency of their green investments and overall sustainability performance (Aouiri et al., 2021).

Green investment is a complex economic activity that combines factors such as the economy, society, and the environment, enabling businesses to pursue economic gains while fulfilling environmental responsibilities (Chen and Ma, 2021). However, achieving a balance between environmental protection and economic benefits is challenging. Varying starting points in green development across nations, coupled with disparities in policy-making and technological capacities, present challenges for developing countries. Moreover, the high costs and long payback periods associated with green investments introduce substantial risk in the long run (Du and Li, 2022). Hence, further research is needed to examine whether the contradiction between economic growth and environmental protection can be addressed through green investment (Li et al., 2022b). While previous research has focused on the influencing factors of green investment (Schaltenbrand et al., 2018; Eyraud et al., 2013) and how investors respond to green investment (Martin and Moser, 2016; Cao et al., 2023), little attention has been given to assessing the future value created by green investments. Our study makes the first empirical attempt to fill this research gap by calculating the future value of green investment, following the spirits of Banker et al. (2011), Lev and Sougiannis (1996), Hanlon et al. (2003), and others. We also analyze the asymmetric effects of green investment at the industry level, providing insightful guidance for businesses to actively pursue green investment and facilitate their sustainable development.

Considering the importance of green credit policy and its impact on green investment efficiency, it is crucial to delve into the actual influence of green credit policy on this efficiency at the micro level. Previous studies on green credit regulations have highlighted their positive implications for firms. Specifically, green credit policy has been found to promote green innovation and its efficiency (Hu et al., 2021), enhance energy efficiency (Tan et al., 2022), and improve environmental performance (Zhang et al., 2021b; Zhang et al., 2021c). However, some research has also identified adverse effects of green credit policy on heavily polluting firms and high-energy-consuming industries through impeding debt financing and innovation initiatives, ultimately leading to a negative impact on financial performance (Li et al., 2019; Wen et al., 2021; Zhu and Lee, 2022). Within the broader context of the green economy, evaluating green investment efficiency calls for a focus on its micro-level impact (Yan et al., 2022). However, existing literature has predominantly examined green investment efficiency at the macro level, such as Fan et al. (2022) measuring it in countries along the “Belt and Road” initiative, and Yang and Ni (2022) exploring the impact of financial development on green investment efficiency in those countries. Meanwhile, research on green investment efficiency at the micro level has primarily centered around topics like green financial development (Chang et al., 2020; He et al., 2019) and equity concentration (Wang et al., 2021). Few studies have investigated the influence of green credit policies on green investment efficiency at the micro level. Therefore, this study aims to address this research gap by utilizing firm-level data to provide insights into the impact of green credit regulation on green investment efficiency.

This study focuses on the Chinese market as it provides an ideal research context for several reasons. China’s rapid economic development over the past few decades has resulted in environmental challenges such as pollution and resource depletion (Ullah et al., 2022; Lee and Wang, 2022; Lee et al., 2022b; Wang et al., 2022). There are also notable instances of environmental violations by firms (Yao et al., 2021a). In response, China has implemented green credit policy in 2012 (Su et al., 2022), making it an ideal research setting to explore the impact of green credit policies on the green investment efficiency. Moreover, China’s immature market environment and unique institutional background offer a solid foundation for studying green credit practices (Chen et al., 2021a; Yao et al., 2021b). Firms, driven by profit, have traditionally lacked proactive environmental awareness, relying on guidance from government and financial institutions to drive their green transition (Zhang et al., 2021a). However, firms in China exhibit lower levels of environmental disclosure quality and may engage in “greenwashing” to meet the requirements of green credit policy (Zhang, 2022). Taken together, the Chinese market provides a suitable context to examine how green credit regulation influences the efficiency of green investments by firms.

This study examines the impact of green credit policy on green investment efficiency using data of Chinese industrial firms from spanning 2009 to 2014. The baseline analysis reveals that green credit policy significantly decreases the efficiency of green investments for heavily polluting firms. A battery of robustness tests are conducted to ensure the reliability of the results. In the heterogeneity analysis, it is observed that the negative effect of green credit policy on green investment efficiency is more pronounced for small, non-state-owned and non-foreign-funded firms. Moreover, the mechanism analysis suggests that the intensity of environmental law enforcement, the level of financial development, and the protection of intellectual property rights can mitigate this negative effect.

Furthermore, this study provides new insights into the future value that green investment can create. The results reveal substantial disparities in the future value of green investments across industries. Labor-intensive industries that are closely linked to consumers’ daily lives exhibit a relatively higher future value of green investments. Conversely, capital-intensive industries like the metallurgical industry demonstrate a comparatively lower future value of green investments.

In summary, our study makes the following contributions to existing literature. First, it discovers a negative relationship between green credit regulation and the efficiency of firms’ green investments. While previous research has mainly focused on green investment and its influencing factors, this study specifically examines the impact of green credit policy on green investment efficiency. Most prior studies suggest that green credit policy helps reduce environmental impact, promotes environmental responsibility, and yield environmental benefits (Nandy and Lodh, 2012); and such policy effectively allocates financial resources (Lv et al., 2021) and encourages firms to pursue green innovation (Hu et al., 2021), leading to mutually beneficial outcomes for the environment and the economy (He et al., 2019). However, our findings show that despite engaging in green investment, heavily polluting firms tend to prioritize symbolic “greenwashing” practices, resulting in decreased investment efficiency. This finding challenges the prevailing notion that green
credit policy inherently enhances green investment efficiency. As such, this paper contributes to the existing literature on green investment efficiency and provides valuable empirical evidence regarding the impact of green credit policy on green investment efficiency.

Second, this study delves into the underlying mechanism of green investment efficiency by examining the roles of environmental law enforcement, financial development, and intellectual property protection. The results show that stricter environmental law enforcement imposes stringent environmental regulations on local firms. In response, firms actively adopt green governance practices and prioritize resource allocation to enhance the effectiveness of their green investments. Besides, financial development not only offers direct financial support to firms but also mitigates information asymmetry risks. This enables firms to enhance resource allocation and investment efficiency. Moreover, intellectual property protection reduces the risk of technology imitation, leading to higher technological returns. As a result, the combined effects of environmental law enforcement, financial development, and intellectual property protection can help alleviate the negative impact of green credit policy on green investment efficiency. It contributes both theoretically and empirically to the promotion of green investment. These findings not only could enrich the literature on green credit regulation but also may provide crucial insights for governments in implementing effective green credit regulations and guiding firms towards enhanced green investment efficiency.

Last but not least, this study makes the first attempt to calculate the future value of green investments and examines its variations across industries. Green investment is a complex management process and economic behavior (Chen and Ma, 2021). On one hand, it can be a reactive response to cope with government environmental regulations, which generates uncertainties and challenges to firms’ financial performance (Berrone et al., 2013; Liao, 2018). On the other hand, it can contribute to a positive social reputation and reduce environmental costs for firms, thereby enhancing their financial performance (Tang et al., 2018). Therefore, the impact of green investments on firms’ future development is still debated. Meanwhile, expanding the scale of green investments is crucial for green transition (Chen and Ma, 2021). Therefore, measuring the future value of green investments has significant theoretical and practical implications for enhancing firms’ green competitiveness. In this regard, this study fills the research gap by exploring the future value of green investments. The results show significant variations in the future value of green investments across industries. Industries that are labor-intensive and closely linked to consumers’ daily lives tend to have higher future value for green investments, while capital-intensive industries such as metallurgical industry show relatively lower future value. Therefore, governments should tailor environmental policies to targeted industries and encourage firms to engage in green investments. It is crucial for firms to consider the future prospects of their industries and avoid short-sighted decision-making. Also, firms should prioritize long-term and strategically advantageous innovative activities to promote their green and sustainable development (Tian et al., 2023).

The remainder of this paper is structured as follows. Section 2 provides a summary of the theoretical background and develops the research hypothesis. Section 3 outlines the empirical design, while Section 4 presents the empirical results. In Section 5, the underlying mechanisms are explored, followed by the calculation of the future value of green investment in Section 6. Finally, Section 7 concludes the paper and provides policy recommendations.

2. Theoretical background and hypothesis

Environmental regulation is effective in balancing the economy and the environment. Rational environmental regulations encourage proactive emission reduction by businesses, thereby fostering long-term economic growth (Liu et al., 2021; Petitjean, 2019). In October 2002, the World Bank introduced the “Equator Principles”, which mandate financial institutions to assess the environmental responsibilities of firms before granting loans. This standard has contributed to the emergence of green credit as a crucial aspect of government environmental regulation. Green credit refers to the practice wherein banks utilize project-related information and the performance of the operating firm as evaluation criteria for loan decisions (Thompson and Cowton, 2004). The objective of green credit is to achieve the harmonious development of finance and the environment by offering differentiated credit services that ensure the proper allocation of financial resources (Nandy and Lodh, 2012).

For firms, bank loans remain their primary source of funding (Zhang et al., 2022a). Under green credit regulations, firms may increase their green investments and shift towards green and low-carbon sectors to qualify for these loans. Green investments are specifically aimed at preserving natural resources and the ecological environment, reflecting a unique form of corporate social responsibility (Martin and Moser, 2016). Despite the increasing trend in environmental investments by firms, these endeavors have not always yielded the anticipated outcomes in terms of environmental impact (Liu et al., 2022a; Chen and Feng, 2019). Xing et al. (2021) uncover “greenwashing” phenomenon in corporate environmental disclosure. This refers to the selective disclosure of environmental information by firms, aimed at hiding their environmental damage and portraying a positive environmental image (Gatti et al., 2021; Szabo and Webster, 2021). Therefore, firms may not necessarily increase their genuine green investments to drive green technology advancements and reduce environmental pollution (Hu et al., 2026; Liao, 2020). Instead, they might prioritize the quantity of green investments rather than their quality to obtain more support for green credit, engaging in symbolic green investments (Jiang and Bai, 2022). Corporate managers may opt for surface-level efforts over substantive investments due to their lower costs and risks. Moreover, firms can still reap advantages from maintaining the perception of environmental responsibility. For example, Russo and Harrison (2005) discovered that firms certified with ISO 14001 actually emitted more toxic air pollutants. This suggests that certification may provide a green image without necessitating substantive actions.

Therefore, under green credit regulations, two distinct patterns of green investment can be observed. First, socially responsible firms tend to engage in real green investments. By investing in sustainable technologies, these firms can lower costs, improve production efficiency, and enhance environmental performance (Yin and Schmeidler, 2009). This, in turn, helps them gain a competitive edge in the green market and achieve long-term sustainable development (Faroq et al., 2021; Hu et al., 2020).

Second, some firms may engage in “greenwashing” by making symbolic green investments. Green investments often involve long payback time and high risk (Du and Li, 2022). Symbolic green investments, on the other hand, have lower costs, shorter development cycles, and practicality (Xue et al., 2023). As green credit regulations are implemented, firms increase their environmental investments. Many firms prioritize scaling up their green investments in the short term to secure more funding, thereby masking their polluting activities. Moreover, evidence shows that numerous firms pursue strategic investments (Hu et al., 2017), but these investments do not necessarily lead to significant technological progress or competitive advantages (Rong et al., 2017). While symbolic green investments may provide short-term benefits, like enhanced green legitimacy and reputation (Walker and Wan, 2012), they lack long-term sustainability (Dahllöf et al., 2019). To improve green investment efficiency, firms must actively participate in environmental activities (Bansal and Clelland, 2004). Therefore, while green credit policy encourages green investments, they can also distort investment behavior and potentially reduce overall efficiency.

Under green credit regulations, heavily polluting firms are more inclined to prioritize superficial efforts over substantive green investments that can generate real green effects to secure more credit
resources. These firms have high energy consumption, large emissions, and significant pollution, which contradicts the principles of energy-saving and emission reduction promoted by green credit regulations (Bai et al., 2019). If banks strictly adhere to green credit policy, they should reduce loans to heavily polluting firms and allocate more credit resources to green and low-carbon firms. The introduction of green credit policy may lead to increased scrutiny and supervision of loan utilization by heavily polluting firms (Szabo and Webster, 2021). When faced with external scrutiny, firms are likely to invest funds in green technologies and actively reduce polluting projects and non-compliant behavior, signaling their commitment to sustainability to banks and the public (Yao et al., 2021a). However, some firms may selectively disclose positive environmental strategies and actions, focusing on surface-level green efforts such as disclosing misleading environmental protection information that are easily observable by stakeholders (Xing et al., 2021). This strategic approach to green investment may ultimately lower green investment efficiency and hinder long-term green development for these firms. In light of these observations, we propose the following hypothesis:

H1. Green credit policy decreases green investment efficiency for heavily polluting firms.

3. Research design

3.1. Sample and data

This study examines the impact of green credit policy on green investment efficiency in heavily polluting firms using Chinese industrial firms from 2009 to 2014 as the research setting. We choose industrial firms for two reasons. First, industrial activities contribute significantly to the economic output of heavily polluting firms.

3.2. Measurement of green investment efficiency

In this study, we quantify green investment efficiency using Data Envelopment Analysis (DEA). DEA is a widely used approach for analyzing efficiency and has been applied in various studies related to renewable energy, environmental challenges, and resource allocation (Lv et al., 2021; Zeng et al., 2018; Zhu et al., 2020). To measure firms' environmental performance, we use the emissions of major pollutants as a reliable indicator. In DEA, where lower emissions are preferred, we consider them as undesirable outputs. To handle this, we adopt the Slack-Based Measure (SBM) model within the DEA framework. The SBM model, developed by Tone (2001), allows us to more accurately assess efficiency by considering both desirable and undesirable outputs. The specification is as follows:

\[
\begin{align*}
\min \rho = & \frac{1}{1 + \frac{1}{\eta} \sum_{i=1}^{m} \frac{y_i}{q_i} + \sum_{i=1}^{m} \frac{a_i}{b_i}} \\
\text{s.t.} & X \delta + s^- = x_a \\
& y \delta - s^- = y_a \\
& B \delta + s^- = b_a \\
& \delta, s^-, s^+ \geq 0
\end{align*}
\]

where, \(\rho\) represents the efficiency value of the evaluated unit DMU, \(x_i\), \(y_i\) and \(b_i\) respectively represent the actual inputs, expected outputs, and undesired outputs of DMU. \(X\), \(Y\), and \(B\) are the optimal target values for inputs, expected outputs, and undesired outputs. \(s^-\) denotes the slack value for inputs, indicating input redundancy, which is the difference between actual inputs and the optimal target inputs. \(s^+\) represents the slack value for expected outputs, indicating a shortfall in the expected outputs, which is the difference between the target value and the actual value. \(s^-\) is the slack value for undesired outputs, indicating an excess of undesired outputs, which is the difference between actual undesired outputs and the target value.

The SBM-DEA model effectively combines financial and environmental information. It treats each sample firm as a Decision Making Unit (DMU). In this model, the firm's green investment is considered as the actual input \((x_i)\), total profit as the actual expected output \((y_i)\), and the annual emissions of pollutants as the actual undesired output \((b_i)\). To accurately reflect the goal of green investment in reducing pollutant emissions, we use an output-oriented DEA model with Variable Returns to Scale (VRS) assumption. This model allows for varying rates of output change compared to input when they change proportionally. In summary, our study introduces three SBM-DEA models with different levels of undesired outputs to assess firms' green investment efficiency. A higher efficiency value indicates that firms' green investments are more effective in reducing pollutant emissions.

3.3. Model setting

The Difference-in-Difference (DID) analysis is widely used for policy evaluation to identify causal relationships (Wen et al., 2022). The introduction of the “Green Credit Guidelines” in 2012, which linked bank credit with corporate pollution, serves as an external event that can impact firm behavior. Therefore, the implementation of the Guidelines provides a quasi-natural experiment for studying the relationship between green credit policy and firms' green investment efficiency. To examine this causal relationship, we run the following DID regression:

\[ \text{GIE} = \alpha + \beta_1 \text{Credit} + \beta_2 \text{Credit} \times \text{Treatment} + \epsilon \]
where \( GIE_{it} \) represents a firm’s green investment efficiency. \( Post_{it} \) is a dummy variable indicating time, where we use the year 2012 as the treatment point when the “Green Credit Guidelines” were introduced. Before 2012, \( Post_{it} \) is set to 0, and from 2012 onwards, it is set to 1. \( Treat_{i} \) is used to group heavily polluting firms. Based on the “Catalogue of Industry Classification Management for Environmental Inspection of Listed Firms (2008)” issued by the Ministry of Ecology and Environment, we identify 16 industries classified as heavily polluting.\(^4\) Firms belonging to these industries are assigned a value of 1 for \( Treat_{i} \), indicating they are in the treatment group. Firms not in these industries are assigned a value of 0, indicating they are in the control group. \( Control_{it} \) represents the control variables. Drawing from previous studies by Hu et al. (2021), Wen et al. (2021), and Yao et al. (2021a), we control for variables such as profit rate (\( Profit \)), firm size (\( Size \)), management expenses (\( Manage \)), financing capacity (\( Collateral \)), fixed asset ratio (\( Fixa \)), and liquidity (\( Liquidity \)). We also control for industry fixed effects and year fixed effects. We report t-values based on robust standard errors clustered by firm. The detailed definitions of the main variables are provided in Appendix A.

3.4 Summary statistics

Table 1 presents descriptive statistics for the main variables. In the sample period of 2009–2014, the median of \( GIE \) is 0.0122, which is lower than the mean of 0.0511. This indicates that most sampled firms have lower green investment efficiency than the average level. Overall, the green investment efficiency of firms tends to be relatively low, indicating inefficient resource allocation in pollution prevention and control. Managers should thoroughly evaluate the firm’s green management processes to minimize the allocation of limited resources to less-valuable activities. In addition, we performed a variance inflation factor (VIF) test.\(^5\) The values of VIFs are all between 1 and 5, indicating that multicollinearity is not a serious concern in this study (Zhang et al., 2022a).

4. Results

4.1 Baseline results

Table 2 presents the baseline regression results for the impact of green credit policy on green investment efficiency. In column (1), the coefficient of \( Post\_Treat \) is –0.0212, which is statistically significant. In column (2), after including the control variables, the coefficient of the interaction term remains significant and negative. This suggests a negative effect of the green credit policy on green investment efficiency in heavily polluting firms, supporting our hypothesis.

Moreover, this study also provides empirical evidence supporting the hypothesis of “greenwashing” through an in-depth analysis of green innovation behavior in heavily polluting firms. The effective implementation of green credit policy requires reliable green innovation information. However, commercial banks face inherent limitations in obtaining firms’ green innovation information, leading to a reliance on specific signals such as the number of green patents (Plumlee et al., 2015). This can inadvertently encourage firms to engage in incremental green innovation (Zhang et al., 2022b) that can hardly generate real green effects with preference for quantity over quality of green innovation (Liao, 2020). In contrast, radical green innovation aims at driving real green transition and focuses on quality over quantity of green innovation (Hu et al., 2020). Meanwhile, driven by the desire to secure green funding, firms may focus on short-term increases in green innovation quantity. As a result, heavily polluting firms may opt for less-challenging incremental green innovation. There are to major types of patents in Chinese patent system: invention patents and utility model patents (Huang, 2010; Huang et al., 2017). Invention patents are more closely tied to breakthroughs and significant contributions in creating new technology products or processes. In contrast, utility model patents involve simpler adjustments or improvements to existing technology. Therefore, we use the number of green invention patents to reflect radical green innovation and the number of green utility model patents to reflect incremental green innovation (Hu et al., 2020; Liao, 2020).

Table 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>SD</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
</tr>
</thead>
<tbody>
<tr>
<td>( GIE )</td>
<td>9144</td>
<td>0.0511</td>
<td>0.1437</td>
<td>0.0044</td>
<td>0.0122</td>
<td>0.0352</td>
</tr>
<tr>
<td>( Profit )</td>
<td>9147</td>
<td>0.0563</td>
<td>0.5797</td>
<td>0.0006</td>
<td>0.0041</td>
<td>0.0209</td>
</tr>
<tr>
<td>( Size )</td>
<td>7404</td>
<td>10.3262</td>
<td>1.7659</td>
<td>9.1692</td>
<td>10.2953</td>
<td>11.4429</td>
</tr>
<tr>
<td>( Lev )</td>
<td>8539</td>
<td>0.0572</td>
<td>0.3370</td>
<td>0.0010</td>
<td>0.0047</td>
<td>0.0203</td>
</tr>
<tr>
<td>( Manage )</td>
<td>8559</td>
<td>8.4758</td>
<td>1.6689</td>
<td>7.3858</td>
<td>8.4403</td>
<td>9.5510</td>
</tr>
<tr>
<td>( Collateral )</td>
<td>8480</td>
<td>0.4357</td>
<td>2.6294</td>
<td>0.0092</td>
<td>0.0383</td>
<td>0.1702</td>
</tr>
<tr>
<td>( Fixa )</td>
<td>8472</td>
<td>0.3844</td>
<td>0.4136</td>
<td>0.1844</td>
<td>0.5095</td>
<td>0.5288</td>
</tr>
<tr>
<td>( Liquidity )</td>
<td>8289</td>
<td>-0.0050</td>
<td>2.9934</td>
<td>-0.0070</td>
<td>0.0202</td>
<td>0.0267</td>
</tr>
<tr>
<td>( Lawenforce )</td>
<td>8047</td>
<td>9.6187</td>
<td>0.7321</td>
<td>9.0316</td>
<td>9.6929</td>
<td>10.1799</td>
</tr>
<tr>
<td>( Finance )</td>
<td>8338</td>
<td>0.1458</td>
<td>0.1770</td>
<td>0.0288</td>
<td>0.0798</td>
<td>0.2007</td>
</tr>
<tr>
<td>( Property )</td>
<td>9156</td>
<td>10.5435</td>
<td>1.2800</td>
<td>9.6843</td>
<td>10.4490</td>
<td>11.7630</td>
</tr>
</tbody>
</table>

Notes: This table presents the descriptive statistics (i.e., number of observations (N), mean, standard deviation (SD), first quartile (P25), median, third quartile (P75)) of the variables. The sample consists of annual observations from the years 2009 to 2014.

\(^4\) The heavily polluting industries include thermal power, steel, cement, electrolytic aluminum, coal, metallurgy, chemicals, petrochemicals, building materials, papermaking, brewing, pharmaceuticals, fermentation, textiles, tanning, and mining.

\(^5\) The results of VIF test are available upon request.
addition, advertisements can enhance the visibility of a firm’s environmental innovation (Liao, 2020). Under the green credit policy, firms may increase their advertising efforts to amplify their green innovation activities. This study quantifies advertising expenses using the natural logarithm of a firm’s advertising expenditure plus one. Table 3 presents the t-test results over the course of the green credit policy for radical green innovation, incremental green innovation, and advertising expenditure in highly polluting firms.

As shown in Table 3, the implementation of the green credit policy in 2012 led to a significant increase in incremental green innovation and advertising expenditure among heavily polluting firms. However, there was no notable change in radical green innovation. These findings suggest that the green credit policy has encouraged heavily polluting firms to focus more on superficial efforts rather than groundbreaking green transition. In response to the policy, some firms may engage in “greenwashing” activities to enhance their green image and comply with regulations (Walker and Wan, 2012). For instance, the coal giant Shenhua Group received environmental awards while neglecting to disclose and address the water and air pollution caused by their projects. This allows them to gain market share under the guise of being environmentally friendly. However, their deceptive practices were exposed by media reports and investigations, leading to penalties and public scrutiny from the Ministry of Ecology and Environment in 2013.

Following the implementation of green credit policy, heavily polluting firms face stricter regulations (Szabo and Webster, 2021). As a result, many firms are actively working to establish a “green” image to improve their environmental standing. However, firms often prioritize surface-level efforts that are easier to implement, have lower costs and risks, and attract more attention, rather than focusing on substantive green investments (Walker and Wan, 2012). While they may yield short-term benefits like enhanced legitimacy and reputation (Walker and Wan, 2012), they lack long-term sustainability (Dahlmann et al., 2019).

To truly improve their green investment efficiency, firms must actively engage in actual environmental practices (Bansal and Clelland, 2004). Therefore, while green credit policy may encourage heavily polluting firms to invest in green initiatives, they may also distort their behavior and reduce overall investment efficiency.

4.2. Robustness tests

4.2.1. Placebo test

We conduct a placebo test following the approach of Chen et al. (2018a) and Cheng et al. (2020) to test the robustness of our DID results. We shift the implementation year of the policy to 2010, so the variable Post is re-defined and the relationship between the policy and green investment efficiency is re-examined. The results in columns (1) and (2) of Table 4 indicate that the coefficient of Post*Treat becomes statistically insignificant. This suggests that the observed decline in firms’ green investment efficiency is indeed attributable to the green credit policy rather than other policies.

In addition, we also conduct a placebo test following Liu et al. (2022b). The approach involves creating virtual time points by shifting the implementation of the “policy” either earlier or later, and running 1000 regressions to examine the distribution of t-values at these virtual shock time points. As shown in Fig. 1, the estimated coefficients demonstrate an inverted U-shaped pattern, symmetrically centered around 0. This indicates that the virtual shocks have no treatment effect on the dependent variable; rather, the effects observed are driven by the external shock and not the placebos. These findings reinforce the robustness and reliability of our estimates, confirming the validity of our key findings.

4.2.2. PSM-DID

To mitigate sample selection bias, we apply the propensity score matching (PSM) method (Su et al., 2022). Specifically, we designate all control variables employed in the baseline regression as covariates for the matching process. To match the samples, we use a k-nearest neighbor matching approach with \(k = 2\) and Mahalanobis distance. The results, presented in column (1) of Table 5, indicate that after matching, the negative effect of green credit policy on green investment efficiency remains statistically significant. This finding reinforces the robustness of our baseline findings.

4.2.3. Alternative measures

We further adopt the approach proposed by Yao et al. (2021a) and replace the dependent variable with alternative measures in our analysis. Specifically, we re-run the regression model using two different sets of variables: one focusing on atmospheric pollutant emissions and the other on water pollutant emissions. The results in columns (2) and (3) of Table 5 consistently show that the coefficient of Post*Treat remains significantly negative, supporting the robustness of our key findings.

4.2.4. Controlling for city fixed effects

To mitigate the potential influence of city-level unobservable factors (Kang et al., 2022), we follow Kim et al. (2021) and introduce city fixed effects in addition to controlling for industry and year fixed effects in our main analysis. The results in column (4) of Table 5 show that the negative relationship between the variables remains significant, providing further support for the robustness of our findings.

4.2.5. Controlling for the time trends of control variables

Moreover, we have concerns regarding the endogeneity of some control variables in the baseline regression. To address this issue, we follow Huber (2018) and include the interaction between the linear time trend and the control variables for the year 2000. The results in column (5) of Table 5 confirm the robustness of our findings. Following Wu et al. (2023) and Wu and Wang (2022), we also conduct a dynamic time test and the results still hold true.

6 The results of the dynamic time test are available upon request.
4.2.6. Eliminating the impact of initial public offerings

To mitigate the potential influence of firms’ initial public offerings (IPOs) on their investment plans, we follow Yan et al. (2022) and exclude firms established in and after 2012 from our sample. We then re-evaluate the impact of green credit policy on green investment efficiency. As shown in column (6) of Table 5, the sign and significance of the interaction term of interest remain consistent, supporting the robustness of our findings.

4.3. Heterogeneity analysis

So far, we have documented the negative impact of green credit regulation on firms’ green investment efficiency. However, green credit policies may have varying effects on firms with different characteristics (Aghion et al., 2012). Previous research has indicated a close relationship between firm characteristics, such as ownership and size, and environmental behavior (Fang et al., 2020). Therefore, this study examines the heterogeneity effects of state ownership, foreign ownership, and firm size on the relationship between green credit policy and corporate green investment efficiency.

4.3.1. State ownership

In China, there is widespread “financial discrimination” against private firms and so banks prefer to lend money to state-owned firms (Cull and Xu, 2003), giving them a competitive advantage in government guarantees and financing (Wu et al., 2022). In contrast, non-state-owned enterprises (non-SOEs) are often seen as having lower creditworthiness. As a result of this credit discrimination, non-state-owned firms receive significantly less credit funding from financial institutions compared to state-owned firms (Cheng et al., 2020). Therefore, after the implementation of green credit policy, stricter lending standards by financial institutions may worsen the credit constraints faced by non-state-owned firms. However, this impact may not be significant for state-owned enterprises (SOEs), which have easier access to credit funding. To investigate the role of state ownership in the impact of green credit policy on firms’ green investment efficiency, this study categorizes firms into state-owned and non-state-owned firms. The empirical results are presented in columns (1) and (2) of Table 6.

The coefficient of Post*Treat is not significant for SOEs, while it is significantly negative for non-SOEs. These findings suggest that green credit policy generates a greater impact on non-SOEs compared to SOEs.

Table 5

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<tr>
<td><em>GIE</em></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>-0.0306***</td>
<td>-0.0347**</td>
<td>-0.0337***</td>
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<tr>
<td></td>
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<td>(0.0070)</td>
<td>(0.0064)</td>
<td>(0.0102)</td>
<td>(0.0170)</td>
<td>(0.0104)</td>
</tr>
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<td>0.0213***</td>
<td>0.0426***</td>
<td>0.0658***</td>
<td>0.0455***</td>
</tr>
<tr>
<td></td>
<td>(0.0068)</td>
<td>(0.0069)</td>
<td>(0.0048)</td>
<td>(0.0107)</td>
<td>(0.0197)</td>
<td>(0.0117)</td>
</tr>
<tr>
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<td>0.0231**</td>
<td>0.0194***</td>
<td>0.0388**</td>
<td>0.0652***</td>
<td>0.0341***</td>
</tr>
<tr>
<td></td>
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<td>(0.0099)</td>
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<td>(0.0186)</td>
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</tr>
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<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Industry FE</td>
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<td>YES</td>
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</tr>
<tr>
<td>Year FE</td>
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</tr>
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<td>City FE</td>
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<td>NO</td>
</tr>
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<td>Observations</td>
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<td>7014</td>
<td>7013</td>
<td>7013</td>
<td>3349</td>
<td>6547</td>
</tr>
<tr>
<td>R²</td>
<td>0.1565</td>
<td>0.1260</td>
<td>0.1430</td>
<td>0.2075</td>
<td>0.1244</td>
<td>0.1304</td>
</tr>
</tbody>
</table>

Notes: This table provides the results of the robustness tests on the impact of green credit policy on green investment efficiency. Column (1) presents the results of the PSM-DID analysis. Columns (2) and (3) show the results when using alternative measures for green investment efficiency. Column (4) includes the results controlling for city fixed effects. Column (5) displays the results of the interaction between linear time trends and the control variables for the year 2000. Column (6) presents the results after excluding firms established in and after 2012. Robust standard errors are reported in parentheses. **, and *** indicate statistical significance at the 5% and 1% levels, respectively.
This could be due to the lower creditworthiness and tighter financial conditions of non-SOEs (Liu et al., 2022c). As lending conditions become more stringent, non-SOEs face greater challenges in obtaining funds from financial institutions (Yao et al., 2021a). As a result, when green credit regulations are introduced, non-SOEs have limited resources to allocate towards environmental initiatives (Chen and Feng, 2019); and they are more likely to engage in superficial green investments to improve their environmental image, rather than focusing on improving the efficiency of green investments. Hence, green credit policy reduces the green investment efficiency of non-state-owned firms.

4.3.2. Foreign ownership

With the rapid economic growth, China has become increasingly attractive to foreign investors. Foreign capital brings advanced technology and effective governance practices that allow for better monitoring of corporate operations (Kong et al., 2020). Firms with higher levels of foreign investment are more likely to prioritize environmental performance and sustainable development (Li et al., 2022a). On the other hand, non-foreign-funded firms often struggle to improve their environmental efficiency due to the lack of environmentally friendly production standards and technologies (Cole et al., 2017). Therefore, under green credit policy, foreign-funded firms are more inclined to adopt clean technologies and invest more in environmentally friendly production practices (Ahmad et al., 2019). Meanwhile, non-foreign-funded firms may face challenges related to internal governance, insufficient green technologies, and increased external regulatory pressure. To examine the role of foreign ownership in the impact of green credit policy on corporate green investment efficiency, we categorize firms into foreign-funded and non-foreign-funded firms (Liu et al., 2022a). The results are provided in columns (3) and (4) of Table 6.

The coefficient of Post*Treat is not statistically significant for foreign-funded firms. However, it is significantly negative for non-foreign-funded firms. This indicates that non-foreign-funded firms are more affected by green credit policy compared to their foreign-funded counterparts. This could be attributed to the lack of advanced green technologies and management capabilities in non-foreign-funded firms. Moreover, they face greater challenges due to stringent environmental regulations and competition from foreign-funded firms, which adds to their survival pressure (Wang and Shen, 2016). Factors such as weak internal governance, insufficient green technologies, and increased external pressures can contribute to a lower green investment efficiency for these firms. Therefore, the implementation of green credit policy reduces the green investment efficiency of non-foreign-funded firms.

4.3.3. Firm size

The size of a firm has a close relationship with its ability to repay bank loans (Fan et al., 2021). Large firms have more financing options, greater financial resources, and higher risk-taking capacity (Zhang et al., 2022a). They are also more cautious with events that could harm their reputation and image, leading them to adopt economically viable green investment strategies (Schaltenbrand et al., 2018). On the other hand, small firms have lower market value and less social visibility, which results in a lack of motivation and ability to prioritize green investment (Schaltenbrand et al., 2018). To explore the impact of green credit policy on green investment efficiency across different firm sizes, this study categorizes firms as large or small firms with the median total assets as the cutoff points. The results are presented in columns (5) and (6) of Table 6.

For large firms, the coefficient of Post*Treat is not significant, while the coefficient of Post*Treat is significantly negative for small firms. This indicates that the impact of green credit policy is more significant on small firms compared to large ones. In face of the regulation pressure from green credit regulations, large firms proactively invest in green initiatives to enhance their image and reputation, thus conveying positive messages to society. Conversely, small firms face greater obstacles in enhancing their environmental performance due to limitations in financing and risk capacity (Fan et al., 2021). Moreover, potential penalties and reputational costs add to the challenges they face. Thus, green credit policy reduces the green investment efficiency of small firms.

5. Underlying mechanisms

To further examine the impact mechanism of green credit regulations on firms' green investment efficiency, we employ a difference-in-difference-in-differences (DDD) method to examine whether the intensity of environmental law enforcement, the level of regional financial development, and intellectual property protection moderate the impact of green credit policy on corporate green investment efficiency. Drawing on the spirit of Luo et al. (2021), we estimate the following DDD regressions: 

\[ GIE_{it} = \beta_0 + \beta_1 \text{Post} + \beta_2 \text{Treat} + \beta_3 \text{Post} \times \text{Treat} + \beta_4 M + \beta_5 \text{Industry} + \beta_6 \text{Year} + \sum \text{Controls}_{i,t} \]

\[ + \sum \text{Industry} + \sum \text{Year} + \epsilon_{it} \]

where \( M \) represents the three moderators, including the intensity of environmental law enforcement (Lawforce), the level of financial development (Finance), and intellectual property protection (Property). The definitions of the other variables remain consistent with Eq. (2).
5.1. Environmental law enforcement

In response to the escalating conflict between environmental protection and economic development, China has established a series of environmental policies and regulations (Hu and Jefferson, 2009). However, policy formulation often involves negotiation among different interest groups, while implementation poses significant challenges. Environmental law enforcement plays a vital role in influencing firms’ pollution emissions. Stringent enforcement can motivate firms to actively engage in environmental governance practices (Borghesi et al., 2015; Shapiro and Walker, 2018). Moreover, environmental law enforcement is an effective tool for addressing negative environmental externalities and improving environmental quality (Greenstone and Hanna, 2014; Jayachandran, 2022). When the government and environmental authorities enhance enforcement, they may impose stricter regulations on firms, including heavier fines for exceeding pollution limits. This intensifies the regulatory environment, increases pollution costs for firms, and prompts them to pursue green transition (Chakraborty and Chatterjee, 2017).

In this study, the level of environmental law enforcement is measured by the number of units (firms) paying pollution fees per year in the province where the firm operates. A higher number of units indicates stronger enforcement. Specifically, Lawenforce denotes the natural logarithm of the number of units plus one. As shown in column (1) of Table 7, the coefficient for Post*Treat is significantly negative (β₁ = −0.3280, p < .01), while the coefficient for Lawenforce*Post*Treat is significantly positive (β₂ = 0.0306, p < .05). This suggests that strengthening environmental law enforcement can mitigate the negative effect of green credit policy on corporate green investment efficiency. The rationale behind this is that stricter enforcement leads to increased environmental regulation and inspections for local firms. To comply with regulations and due to resource constraints, firms actively engage in green governance and allocate resources efficiently, thus enhancing their green investment efficiency (Chen and Feng, 2019). Therefore, stronger environmental law enforcement positively influences firms’ green behavior and resource allocation, thereby mitigating the negative effect of green credit regulation on firms’ green investment efficiency.

5.2. Financial development

Firms’ green development is influenced not only by internal factors but also by the level of local financial development (Demirgüç-Kunt and Maksimovic, 1998). First, regions with well-developed financial systems provide firms with greater access to financing options, helping to alleviate financing constraints (Lv et al., 2021). Second, higher levels of financial development enable better information gathering and processing, allowing for the identification of efficient and innovative projects. In turn, firms increase investments in advanced production technologies and projects, driving the progress of green and clean technologies (Ma and Stern, 2008). Lastly, financial development reduces information asymmetry, improving the efficiency of capital allocation (Love, 2003). Therefore, financial development could enhance green investment efficiency by increasing funding availability, promoting green technology investments, and reducing information asymmetry risks.

In this study, the level of financial development (Finance) is measured by the proportion of financial institutions deposit and loan balances to total GDP in the city where the firm is located. In column (2) of Table 7, the coefficient for Post*Treat is significantly negative (β₁ = −0.0436, p < .01), while the coefficient of Finance* Post*Treat is significantly positive (β₂ = 0.0817, p < .05). Therefore, an improvement in local financial development can help reduce financing constraints, stimulate investments in green technology, and enhance capital allocation efficiency, thereby mitigating the negative effect of green credit policy on firms’ green investment efficiency.

5.3. Intellectual property protection

China has developed a robust system for protecting intellectual property rights (IPR), leading to an increase in patent applications filed with the Intellectual Property Administration (Liegsalz and Wagner, 2013). However, the enforcement of IPR protection may vary across regions in China (Ang et al., 2014). Strong IPR protection reduces the risk of technology imitation and encourages firms to invest in technology-intensive green industries, thereby promoting their green innovation (Grimaldi et al., 2021; Sampat and Williams, 2019). Therefore, the level of IPR protection in a region may influence firms’ green transition.

We measure intellectual property protection using the number of patents granted by local Intellectual Property Administration each year. A higher number of granted patents indicates stronger IPR protection (Liegsalz and Wagner, 2013). Property represents the natural logarithm of the number of granted patents plus one. In column (3) of Table 7, the coefficient for Post*Treat is significantly negative (β₁ = −0.2159, p < .01), while the coefficient for Property* Post*Treat is significantly positive (β₂ = 0.0173, p < .05). We also use the natural logarithm of the cumulative number of granted patents plus one as an alternative measure of IPR protection, and the results remain consistent. The results suggest that stronger IPR protection reduces the risk of technology imitation or replication (Grimaldi et al., 2021), encouraging firms to

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Post</strong>Treat*Lawenforce</td>
<td>0.0306** (0.0125)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post*Lawenforce</td>
<td>−0.0183 (0.0112)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treat*Lawenforce</td>
<td>−0.0259*** (0.0089)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Post</strong>Treat*Finance</td>
<td>0.0817** (0.0397)</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>−0.0751** (0.0331)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treat*Finance</td>
<td>−0.0160 (0.0326)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Post</strong>Treat*Property</td>
<td>0.0173** (0.0097)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post*Property</td>
<td>−0.0141* (0.0073)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treat*Property</td>
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<td></td>
</tr>
<tr>
<td><strong>Post</strong>Treat</td>
<td>−0.3280*** (0.0120)</td>
<td>−0.0436*** (0.0128)</td>
<td>−0.2159** (0.0840)</td>
</tr>
<tr>
<td>Post</td>
<td>0.2199** (0.1098)</td>
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<td>0.1929** (0.0818)</td>
</tr>
<tr>
<td>Treat</td>
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<td>0.0291* (0.0149)</td>
<td>0.0810 (0.0525)</td>
</tr>
<tr>
<td>Lawenforce</td>
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</tr>
<tr>
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<td>0.0225 (0.0259)</td>
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<td></td>
</tr>
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<td>Property</td>
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<td></td>
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</tr>
<tr>
<td>Year FE</td>
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<td>YES</td>
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<td>7002</td>
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<tr>
<td>R²</td>
<td>0.1301</td>
<td>0.1248</td>
<td>0.1298</td>
</tr>
</tbody>
</table>

Note: This table presents the regression results of the underlying mechanisms. Column (1) shows the results of the environmental law enforcement mechanism, column (2) shows the results of the financial development mechanism, and column (3) shows the results of the intellectual property protection mechanism. Robust standard errors are reported in parentheses. **, *, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.
invest in green R&D activities. Hence, this helps mitigate the negative effect of green credit regulation on corporate green investment efficiency.

6. Future value of green investment

Green investment is a unique form of corporate social responsibility (Martin and Moser, 2016) and a complex management process and economic behavior (Chen and Ma, 2021). On one hand, it can be seen as a reactive response to government environmental regulations (Berrone et al., 2013; Liao, 2018), and it requires substantial funding and involves significant financial risks. On the other hand, it helps firms build a positive reputation, reduce environmental compliance costs, and improve economic performance (Tang et al., 2018). Therefore, the impact of green investment on corporate development is still uncertain. Moreover, the diverse characteristics of industries contribute to variations in green investment efficiency (Liu et al., 2022a). Therefore, this study makes the first attempt to address the following questions: how much value does corporate green investment generate? Does the value created by green investment differ across industries?

To address these questions, we first calculate the future value of green investments following the spirit of Banker et al. (2011). The measurement of the future value created by current green investments is derived using the model proposed by Lev and Sougiannis (1996):

\[
O(I/TA)_{it} = a_0 + a_1(1/TA)_{it-1} + \sum_{k=1}^{n} a_{2k} (GI/TA)_{it-k} + e_{it}, \tag{4}
\]

where \( O(I) \) is the operating income, \( GI \) is green investment, and \( TA \) is total assets. In addition, to mitigate endogeneity concerns, we employ a two-stage least squares (2SLS) approach following Lev and Sougiannis (1996). In the first stage, we instrument \((GI/TA)_{it}\) using its quadratic term. This choice of instrument is based on the method employed by Hanlon et al. (2003), which uses higher-order moments of endogenous variables as instruments. Specifically:

\[
(GI/TA)_{it} = a + b(GI/TA)_{it-1}^2 + u_{it}, \tag{5}
\]

In this second stage, we estimate Eq. (4) using the predicted value \((GI/TA)_{it}\) from Eq. (5) as an instrument for \((GI/TA)_{it-1}\). Specifically, we introduce year fixed effects and estimate Eq. (4) for each industry using two-digit National Economic Industry Classification Codes. We employ an unrestricted distributed lag model to estimate the lagged number \((n)\) and so the corresponding coefficients of the lagged \(GBs\) (Hanlon et al., 2003). Then, we select the best-fitting model based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Finally, we estimate the future value of green investments based on the lag coefficients identified in the industry-specific model. Assuming a discount rate of 10% (Banker et al., 2011), the future value of green investment, denoted as \( \sum_{k=1}^{n} a_{2k} (GI/TA)_{it-k} \), captures the impact of past green investment on the current period.

To estimate the future value of green investment, we first determine the lag structure of green investment for each firm. The lag structure indicates how many years it takes for current green investment to affect future returns. Consistent with Banker et al. (2011), we assume the lag structure is the same for firms with each two-digit industry code. Also, we exclude the bottom 5% of \( OI/TA \) and \( GI/TA \) values and remove industries with <20 samples to minimize the impact of extreme values and small sample sizes. Table 8 presents the estimation results for each industry.

<table>
<thead>
<tr>
<th>Industry</th>
<th>( a_{20} )</th>
<th>GI future value</th>
<th>Adj. ( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturing of cultural, educational, and sports goods</td>
<td>2.7406</td>
<td>2.4857</td>
<td>0.4704</td>
</tr>
<tr>
<td>Textile, clothing, and apparel manufacturing</td>
<td>2.7594</td>
<td>1.7242</td>
<td>0.1681</td>
</tr>
<tr>
<td>Leather, fur, feather, and their product manufacturing</td>
<td>4.7862</td>
<td>1.3488</td>
<td>0.2905</td>
</tr>
<tr>
<td>Comprehensive utilization of waste resources</td>
<td>4.5388</td>
<td>0.8628</td>
<td>0.4718</td>
</tr>
<tr>
<td>Computer, communication, and other electronic equipment manufacturing</td>
<td>2.8597</td>
<td>0.5330</td>
<td>0.0982</td>
</tr>
<tr>
<td>Non-metallic mineral mining and quarrying</td>
<td>3.8092</td>
<td>0.4783</td>
<td>0.1200</td>
</tr>
<tr>
<td>Manufacturing of chemical raw materials and chemical products</td>
<td>1.7272</td>
<td>0.4242</td>
<td>0.0843</td>
</tr>
<tr>
<td>Production and supply of electricity and heat</td>
<td>0.5114</td>
<td>0.2084</td>
<td>0.0357</td>
</tr>
<tr>
<td>Wood processing and wood, bamboo, rattan, palm, and straw products manufacturing</td>
<td>1.9912</td>
<td>0.2044</td>
<td>0.1355</td>
</tr>
<tr>
<td>Ferrous metal smelting and rolling processing</td>
<td>2.2424</td>
<td>0.1798</td>
<td>0.1260</td>
</tr>
<tr>
<td>Non-ferrous metal smelting and rolling processing</td>
<td>1.6901</td>
<td>0.1241</td>
<td>0.0711</td>
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<td>Textile Manufacturing</td>
<td>2.3705</td>
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<td>Food manufacturing</td>
<td>1.7903</td>
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<td>0.0588</td>
</tr>
<tr>
<td>Pulp and paper products manufacturing</td>
<td>3.3878</td>
<td>0.0401</td>
<td>0.2032</td>
</tr>
<tr>
<td>Non-metallic mineral products manufacturing</td>
<td>2.5889</td>
<td>0.027</td>
<td>0.1201</td>
</tr>
<tr>
<td>Printing and reproduction of recorded media</td>
<td>2.1374</td>
<td>−0.0133</td>
<td>−0.0917</td>
</tr>
<tr>
<td>Pharmaceutical manufacturing</td>
<td>2.0845</td>
<td>−0.041</td>
<td>0.0827</td>
</tr>
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<td>Beverage manufacturing</td>
<td>2.5264</td>
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<td>1.8879</td>
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<td>General equipment manufacturing</td>
<td>2.7128</td>
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</tr>
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<td>Electrical machinery and equipment manufacturing</td>
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<td>Automobile manufacturing</td>
<td>3.9390</td>
<td>−0.3330</td>
<td>0.2242</td>
</tr>
<tr>
<td>Processing of agricultural and sideline products</td>
<td>1.5991</td>
<td>−0.3812</td>
<td>0.0549</td>
</tr>
<tr>
<td>Chemical fiber manufacturing</td>
<td>3.0971</td>
<td>−0.3837</td>
<td>0.2583</td>
</tr>
<tr>
<td>Rubber and plastic products manufacturing</td>
<td>2.1512</td>
<td>−0.4139</td>
<td>0.0035</td>
</tr>
<tr>
<td>Petroleum processing, coking, and nuclear fuel processing</td>
<td>2.6563</td>
<td>−0.4296</td>
<td>0.1200</td>
</tr>
<tr>
<td>Railway, shipbuilding, aerospace, and other transportation equipment manufacturing</td>
<td>3.7909</td>
<td>−0.4399</td>
<td>0.2375</td>
</tr>
<tr>
<td>Coal mining and washing</td>
<td>2.1178</td>
<td>−0.4602</td>
<td>0.1243</td>
</tr>
<tr>
<td>Instrumentation manufacturing</td>
<td>1.4955</td>
<td>−0.6421</td>
<td>0.0751</td>
</tr>
<tr>
<td>Furniture manufacturing</td>
<td>4.0329</td>
<td>−0.6750</td>
<td>0.3623</td>
</tr>
<tr>
<td>Ferrous metal mining and quarrying</td>
<td>2.8585</td>
<td>−0.6972</td>
<td>0.1463</td>
</tr>
<tr>
<td>Non-ferrous metal mining and quarrying</td>
<td>1.2637</td>
<td>−0.9431</td>
<td>0.0380</td>
</tr>
<tr>
<td>Special equipment manufacturing</td>
<td>3.3730</td>
<td>−0.9445</td>
<td>0.1861</td>
</tr>
<tr>
<td>Other manufacturing</td>
<td>2.5329</td>
<td>−1.6299</td>
<td>0.1715</td>
</tr>
</tbody>
</table>

Note: This table displays the regression coefficients for each industry from 2009 to 2014.

The textile, clothing, and apparel manufacturing industry, being closely connected to consumers, can generate a higher future value for green investment. This industry holds significant economic importance and serves as a livelihood source for many people in China (Ruan et al., 2022). As environmental pollution, resource scarcity, and strict
regulations become more prominent, it is crucial for the industry to shift towards green practices and sustainable development (Ruan et al., 2022). According to the “2021/2022 China Textile Industry Development Report”, the sector has made notable progress in optimizing its energy structure. With 72.5% of energy coming from secondary sources and a 25.5% reduction in comprehensive energy consumption per unit of output, the industry has also achieved significant reductions in wastewater and pollutant emissions. The future value of green investment in the textile, clothing, and apparel manufacturing industry is driven by several factors. On one hand, many brands in this industry have incorporated green standards into their supply chains, urging suppliers to adopt sustainable production practices. Also, advancements in clean production technologies enable energy savings and improved efficiency, thereby facilitating the development of green supply chains. On the other hand, consumers are increasingly socio-environmentally conscious (Shen et al., 2014) and recognize the importance of emissions reduction (Cao et al., 2023; Tao et al., 2022). This consciousness directly influences their purchasing decisions, and a green supply chain enhances their willingness to support sustainable products (Shen et al., 2014). Besides, textile firms pursue green investment strategies to both attract consumers and maximize profits. Therefore, the future value of green investment in the textile, clothing, and apparel manufacturing industry is relatively high.

In contrast, capital-intensive industries like metallurgy (including ferrous metal mining and non-ferrous metal mining and quarrying industry) tend to have relatively lower future value for green investment. The metallurgical industry in China is a significant contributor to both energy consumption and environmental pollution (Feng et al., 2018). Its extensive growth model has led to severe environmental issues (Feng et al., 2019). According to the “China Metallurgical Engineering Industry Market Outlook and Investment Strategy Analysis Report”, despite some advancements in technology and green development, the industry continues to face challenges, including increasing resource and environmental burdens, and a high-carbon energy structure. From a regulatory perspective, the “2021 Central Ecological and Environmental Protection Inspection Report” highlighted severe issues related to environmental responsibility, violations, and ecological damage by major metallurgical firms like Shougang, Baosteel, and Hesteel. These firms were then required to rectify their pollution projects and faced fines totaling 1.3 million yuan. At the corporate level, metallurgical firms are often large state-owned firms with inherent political connections (Chen et al., 2018b). They can use these connections to seek protection and engage in superficial compliance behaviors. Therefore, the future value of green investment in these sectors is relatively low.

7. Conclusions and policy implications

This study investigates the impact of green credit regulations on green investment efficiency in Chinese industrial firms from 2009 to 2014. The baseline results indicate that green credit policy reduces the efficiency of green investment for heavily polluting firms. A battery of robustness checks is conducted, including placebo tests, PSM-DID analysis, alternative measures, controlling for city fixed effects, and controlling for time trends, etc. The main findings remain valid against these robustness checks. Heterogeneity analysis further indicates that this negative impact is more pronounced in small, non-state-owned, and non-foreign-funded firms. Moreover, the underlying mechanism analysis suggests that the strength of environmental law enforcement, the level of local financial development, and the protection of intellectual property rights can help alleviate the negative impact of green credit policy on firms’ green investment efficiency. Furthermore, this study explores the future value that green investment can create. It highlights the substantial variations across industries. Labor-intensive industries with a direct impact on consumers’ daily lives tend to possess higher future value for green investment. Conversely, capital-intensive industries, such as the metallurgical industry, exhibit relatively lower future value for green investment.

Our findings shed light on the “dark side” of green credit regulations, providing valuable insights for governments to refine the design of green finance policies and facilitate resource allocation of businesses. First, the government needs to enhance and optimize green credit regulations to maximize their effectiveness. Our study reveals that green credit policy decreases the efficiency of green investments among heavily polluting firms, possibly due to superficial compliance behaviors. Therefore, stricter penalties for “greenwashing” initiatives, along with increased green legitimacy requirements for polluting firms, are essential to combat superficial compliance behaviors.

Second, addressing the asymmetric effects of the policy is crucial. Our heterogeneity analysis reveals that green credit policy primarily affects the green investment efficiency of small, non-state-owned, and non-foreign-funded firms. Accordingly, tailored controls and performance monitoring should be implemented for these firms to encourage voluntary social responsibility adoption and so green transformation.

Third, environmental law enforcement, financial development, and intellectual property protection are identified as underlying mechanisms for green credit effectiveness. Therefore, the government should consider these factors when formulating and implementing environmental policies and regulations. Strengthening supervision and penalties for heavily polluting firms, directing financial resources towards greener investment, and safeguarding intellectual property rights are essential components of a comprehensive approach.

Last but not least, industry-specific environmental policies that encourage active green investment by firms are critical. For labor-intensive industries, seizing opportunities in the green market and enhancing competitiveness through the development of eco-friendly products and innovative green technologies is recommended. For capital-intensive industries, improving the intensity and standards of environmental regulations, promoting the transition towards emerging green technology firms, and formulating sustainable strategies for green development are necessary.

This study also has a few limitations. First, the data used in this study does not cover recent events such as the COVID-19 pandemic and its impact on green investment. Future research should consider these factors. Second, as green credit regulations are relatively new market-based environmental regulatory tools in China, and there is currently no mandatory requirement for firms to disclose specific green credit data, future studies could benefit from using more comprehensive and detailed micro-level data to further explore this topic.

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CRediT authorship contribution statement

Jinfang Tian: Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing. Siyang Sun: Data curation, Formal analysis, Software, Writing – original draft. Wei Cao: Data curation, Writing – review & editing. Di Bu: Supervision, Writing – review & editing. Rui Xue: Conceptualization, Project administration, Supervision, Writing – review & editing.
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Appendix A. Variable definitions

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definitions</th>
</tr>
</thead>
<tbody>
<tr>
<td>GIF</td>
<td>Green investment efficiency, calculated based on the SBM-DEA model.</td>
</tr>
<tr>
<td>Post</td>
<td>An indicator variable takes the value one after the green credit policy, and zero otherwise.</td>
</tr>
<tr>
<td>Treat</td>
<td>The ratio of total profits to industrial sales value.</td>
</tr>
<tr>
<td>Size</td>
<td>Natural logarithm of a firm's net fixed assets.</td>
</tr>
<tr>
<td>Lee</td>
<td>Natural logarithm of the book value of total assets.</td>
</tr>
<tr>
<td>Manage</td>
<td>The sum of net fixed assets and inventory value divided by the book value of total assets.</td>
</tr>
<tr>
<td>Collateral</td>
<td>The book value of fixed assets divided by the book value of total assets.</td>
</tr>
<tr>
<td>Liquidity</td>
<td>The difference between current assets and current debt divided by the book value of total assets.</td>
</tr>
<tr>
<td>Loan/force</td>
<td>Natural logarithm of the number of units paying pollution fees per year in the province where the firm operates plus one.</td>
</tr>
<tr>
<td>Finance</td>
<td>The proportion of annual financial institutions deposit and loan balances to GDP in the city where the firm is located.</td>
</tr>
<tr>
<td>Property</td>
<td>Natural logarithm of the number of granted patents plus one.</td>
</tr>
</tbody>
</table>

References


Fang, J., He, H., Li, N., 2020. China’s rising IQ (innovation quotient) and growth: firm-level evidence. J. Dev. Econ. 147, 105261.


