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Low-Carbon Governmental Policies and Cost of Debt: Evidence from China

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Abstract

This paper uses the staggered difference-in-differences design to investigate the effects of the low-carbon city pilot (LCCP) policy on the cost and underlying mechanisms of debt financing for enterprises. Our findings show that the LCCP significantly decreases the debt cost of enterprises through enhancements in Environmental, Social, and Governance (ESG) performance and the reduction of information asymmetry. Additional analysis indicates that the LCCP's ability to reduce the cost of debt is particularly pronounced for firms with higher agency costs and those located in China's eastern regions. This study offers evidence for assessing the effectiveness of low-carbon policies and suggests recommendations to policymakers seeking to enhance the design and implementation of LCCP, thereby contributing to the green development of enterprises and regions.

Keywords: Low-Carbon; Cost of Debt; Sustainable Development; ESG Performance; Information Asymmetry

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1. Introduction

As global climate change worsens, the Chinese government has prioritized green and low-carbon development as a core national strategy, actively implementing policies to advance its environmental governance objectives (Aydin et al., 2025). To reduce carbon emissions and achieve green urban development, the Chinese government established three rounds of LCCPs in 2010, 2012, and 2017. These pilot regions were required to calculate and determine their total greenhouse gas emissions targets and develop a supporting system for carbon emissions trading pilot programs. Therefore, while striving to increase revenue, companies must also enhance green innovation, strengthen environmental protection, reduce carbon emissions, and prioritize their long-term sustainable development (Wagner, 2007; Hojnik & Ruzzier, 2016).

In the process of green transformation, companies inevitably need financing to support transformations, such as green technology upgrades through equipment improvements and adjustments to industrial structures. Therefore, financing costs are a key factor for firms to consider during their green transformation. Debt financing is the most direct way for firms to obtain external capital. Reducing the cost of debt will drive companies toward low-carbon transformation. However, research is lacking on the impact of government policies, such as low-carbon city pilots, on financing costs during implementation and the mechanisms through which these policies are implemented. This paper examines how LCCP affects the debt financing costs of enterprises and its impact channels. Furthermore, the phased implementation of low-carbon city pilots provides an ideal quasi-natural experimental setting for research, allowing for the application of a staggered difference-in-differences (DID) model (Ma et al., 2021) to mitigate endogeneity issues.

This study utilizes data from Chinese A-share listed companies from 2007 to 2020, employing a staggered DID design, to examine the impact of LCCPs on the cost of debt. The results show that the LCCP significantly reduces firms' cost of debt. Further analysis indicates that the LCCP reduces the cost of debt through two channels: improving corporate ESG performance and reducing information asymmetry. Cross-section analysis indicates that this effect is most pronounced for firms with higher agency costs and those located in China’s eastern regions.

This paper makes the following contributions. First, it expands the literature on the evaluation of low-carbon city pilot policies. Previous literature had primarily examined the direct impact of low-carbon city policies on pilot regions and their local business environments (Chen et al., 2021; Liu et al., 2022). This study evaluates the impact of macro-level low-carbon policies on micro-enterprise behavior, extending the findings of Stechemesser (2024) and identifying the micro-level economic consequences of low-carbon policies.

Second, this study highlights mechanisms by which macro-level policies influence micro-enterprises. It explores the drivers of policy implementation from both internal and external perspectives, encompassing factors such as ESG performance and information asymmetry, enhances the synergy between government and companies in policy implementation, and provides targeted recommendations for promoting cost control.

Finally, it provides references and recommendations for government implementation and improvement of low-carbon policies. This study finds that low-carbon pilot policies can provide potential financing support for enterprises, promote their green development, and provide experience for future expansion and improvement of pilot policies. At the same time, it can inform the company’s future trajectory. Companies that conform to future green development trends have lower financing costs and are more likely to achieve sustainable development.

2. Literature Review and Hypothesis Development

2.1. Literature Review

Environmental regulations promote both environmental quality and economic development. Shapiro and Walker (2018) attribute a 60% decline in U.S. manufacturing emissions between 1990 and 2008 to stringent environmental rules. Environmental regulations can significantly reduce pollution while stimulating productivity and facilitating industrial upgrading (Brock & Taylor, 2005; Dean et al., 2000). A key mechanism is innovation—environmental policies encourage advances in production and emission-control technologies, thereby strengthening enterprise environmental and economic performance (Hamamoto, 2006; Horbach, 2008).

It warrants further exploration that the impact of environmental policies has extended beyond production and emissions, systematically reaching into the realm of enterprises' financial decisions and cost structures. Policy-driven environmental and operational shifts not only directly impact an enterprise's debt costs but also systematically influence its weighted average cost of capital and capital expenditure decisions. Environmental policies can reshape a firm’s financing structure by simultaneously affecting its cost of equity and cost of debt, though often through distinct channels and with varying intensity (Hu et al., 2025). For instance, while stringent regulations may elevate perceived operational and compliance risks, thereby increasing the cost of equity demanded by shareholders (Duarte et al., 2008; Liu et al., 2025). They can also incentivize improved environmental transparency and performance, which in turn may reduce information asymmetry and lower risk premiums demanded by debt holders (Zhang et al., 2025). Consequently, the net effect on a firm's overall cost of capital hinges on how these opposing forces interact within specific policy and market contexts, underscoring the importance of examining both financing dimensions comprehensively.

As an environmental regulations policy, the LCCP provides a practical framework for low-carbon transition, incentivizing enterprises to develop and adopt green technologies. Studies show that the LCCP significantly reduces enterprise carbon intensity and enhances environmental compliance (Bu et al., 2020; Yang et al., 2023). It also pressures enterprises to improve environmental transparency and disclosure (Fang et al., 2021). These environmental and operational shifts under the LCCP have direct implications for enterprises' cost of debt. Improved environmental performance and disclosure can reduce perceived risk among lenders, leading to more favorable loan conditions (Sharfman & Fernando, 2008; Goss & Roberts, 2011). Conversely, enterprises facing high cost of debt may signal financing difficulties or elevated risk, both of which can hinder investment and innovation (Deumes et al., 2008; Raimo et al., 2021). Variations in the cost of debt often reflect disparities in enterprises' ability to obtain financing, with deviations from industry averages affecting competitiveness and growth (LaRosa et al., 2014). Enterprise governance and transparency moderate these effects, underscoring the interrelatedness of environmental performance, financial constraints, and debt financing (Jiang et al., 2016). Thus, the LCCP not only advances environmental goals but also shapes enterprises' financial outcomes through its influence on innovation, risk perception, and debt financing conditions.

2.2. Institutional Context

In a State Council Executive Meeting on November 26, 2009, China set national greenhouse gas emission reduction targets to be achieved by 2020. Subsequently, the National Development and Reform Commission launched three rounds of LCCP. In July 2010, November 2012, and January 2017, it expanded the program from a few pilot regions to 81 cities nationwide. As illustrated in Figure 1, this expansion reflects a deliberate policy evolution from experimentation to broader strategic diffusion.

<Insert Figure 1>

The selection process for pilot cities evolved from top-down designation in the first round to a competitive, expert-reviewed application system in the second and third rounds. Pilot regions were required to tailor their strategies based on local resource endowments, development stages, and industrial structures. The administrative focus shifted from provincial capitals and major municipalities to more prefecture-level cities, improving implementation feasibility. The pilots encompassed diverse geographical regions, including economic hubs, ecological preservation zones, resource-based cities, and industrial bases, indicating no significant selection bias. The list is shown in Table 1.

< Insert Table 1>

The LCCP promotes green technological innovation, restructures low-carbon industrial systems, upgrades urban energy consumption, enhances energy efficiency, and ultimately supports high-quality economic development (Khanna et al., 2014; Li et al., 2018). Each pilot city formulated tailored strategies in alignment with these objectives. For instance, Tianjin established special funds and leveraged market mechanisms to encourage enterprise participation; Hubei prioritized emissions accounting, carbon trading pilots, and low-carbon technology adoption; Liaoning and Shanghai introduced similar measures targeting industrial restructuring and energy conservation at the enterprise level. Enterprises are encouraged to reduce energy-intensive activities, increase their investment in low-carbon sectors, and accelerate R&D in green technologies.

2.3. Hypothesis Development

The LCCP emphasizes the necessity of developing and adopting low-carbon technologies. Local governments have introduced supportive policies to facilitate the enterprise transition to low-carbon practices. For instance, Hangzhou established a low-carbon industry investment fund with an initial size of 2 billion yuan, potentially expanding to more than 5 billion yuan. Hubei Province implemented financial guarantees, optimized credit structures, and promoted greenhouse gas management to foster low-carbon industries. These measures are often taken in exchange for preferential credit terms. But at the same time, there are uncertainties and risks in enterprises' green transformation.

The LCCP encourages enterprises to standardize their carbon emissions disclosures, optimize industrial structures, and enhance green competencies. The results of these measures are reflected in improved ESG performance, which mitigates business risks and strengthens sustainable operational capacity. As a comprehensive evaluation framework, ESG incorporates environmental, social, and governance dimensions, aligning with the LCCP emphasis on balanced development. Improved ESG performance helps enterprises reduce resource consumption, increase operational efficiency, and signal stronger risk management to investors. Consequently, enterprises with robust ESG practices often benefit from lower debt financing costs, as lenders perceive them as less risky (Ghoul et al., 2017; Edmans, 2023).

Furthermore, the LCCP guides enterprises to reduce information asymmetry by mandating systematic reporting on greenhouse gas emissions. Pilot regions are required to develop rigorous emission inventories and monitoring systems, increasing the transparency around enterprise environmental performance. Enhanced disclosure alleviates investor uncertainty, reduces monitoring costs, and diminishes credit risk premiums. Empirical evidence suggests that greater transparency correlates with lower cost of debt (Jiang et al., 2016).

Therefore, the LCCP is expected to lower enterprises' cost of debt through elevated ESG performance and improved informational transparency. Accordingly, we state the following hypothesis in its alternative form:

H1: The LCCP reduces the enterprises' cost of debt.

Further, LCCP strengthens the regulation of carbon emissions of enterprises. There is uncertainty in the improvement and upgrading of green technology in enterprises. Enterprises with less advanced green technology may find it difficult to comply with strict environmental regulations. Given the uncertainty of the sustainable development of the enterprise, creditors will require higher interest rates in the debt financing of the enterprise to assuage the uncertainty, which will increase the cost of debt.

The environmental protection by enterprises is an important indicator for credit approval, and the credit threshold is controlled by raising interest rates. As a result, the cost of debt of high-polluting enterprises will rise, especially for new borrowing and long-term debt financing (Michael et al., 2005). According to the Shenzhen Medium- and Long-term Plan for Low-carbon Development (2011 – 2020), the government can deter the investment behavior of high-pollution industries by imposing punitively high interest rates, which can mitigate the production output of the most polluting industries, thus curbing the debt financing and investment of those enterprises.

Companies operating in LCCP areas are mandated to undertake green technological transformation to meet local politicians, a process that inherently entails business risks. In the interim, the negative impact on enterprises' production is discernible, leading to heightened uncertainty in green transformation. In this case, the company's operating performance may decline, resulting in an increase in its risk and consequently higher debt costs. We therefore posit an opposing hypothesis stated in its alternative form:

H2: The LCCP increases the enterprises’ cost of debt.

3. Methodology

3.1. Data and Sample

The data utilized in this study are from the China Stock Market & Accounting Research Database, Wind, and National Bureau of Statistics databases. The sample encompassed the listed enterprises on the A-share market in China for the time period 2007 to 2020. To ensure data quality, following procedures were implemented for data processing and screening: (1) exclusion of the financial companies, because of differences in asset structures and financial data compared with enterprises in other industries; (2) exclusion of ST and *ST companies: enterprises designated as ST or *ST, which indicate potential delisting risks due to unsatisfactory performance; (3) elimination of enterprises with missing data; and (4) trimming of outliers: the upper and lower 1% of the distribution of primary continuous variables was trimmed. After data processing, 3,226 enterprises with 22,733 enterprise-years were obtained.

The treatment group comprised enterprises covered by the LCCP, encompassing a total sample of 15,933 enterprise-years, whereas the control group comprised a sample of 6,800 enterprise-years.

3.2. Variable Measurement

Cost of debt was treated as a proxy indicator (*DebtCost*) (Minnis, 2011). This study adopted the net finance cost ratio as a proxy indicator. The LCCP variable (*Did*) was defined as an indicator variable. For a given city *i*, if it was chosen to participate in the LCCP during year *t*, the *Did* variable assumes a value of 1 for that year and all subsequent years. Conversely, for years in which the city was not a part of the LCCP, the *Did* variable is assigned a value of 0.

3.3. Research Design

To validate hypothesis ***H1***, a staggered DID model was developed to evaluate the LCCP's influence on the cost of debt.

$$DebtCost_{it} = \beta_0 + \beta_1 Did_{it} + Control\,Variables_{it} + \varepsilon_{it} \qquad (1)$$

Following Beck et al. (2010), the control variables were selected from various dimensions, including enterprise characteristics, financial conditions, and enterprise governance. Both year (*YEAR*) and firm (*Firm*) fixed effects were controlled. The appendix provides detailed definitions of all the variables.

4. Empirical Results

4.1. Descriptive Statistics

Table 2 presents the descriptive statistics for the main variables. The mean *DebtCost* is 0.025, with a median of 0.024 and a standard deviation of 0.015, indicating a relatively concentrated distribution. The treatment group contains 15,933 observations, accounting for 70.09% of the total sample, reflecting the broad coverage and sustained impact of the LCCP on China's A-share listed companies and capital markets.

To examine differences between the treatment and control groups, we performed a t-test on means and a Z-test on medians for *DebtCost*. The mean *DebtCost* in the treatment group is 0.025, compared to a difference of 0.002 to 0.027 in the control group. Although this absolute difference appears modest, it translates to a reduction of approximately 8% relative to the treatment group's mean, which is economically meaningful. Similarly, the median *DebtCost* of 0.024 in the treatment group is lower than the 0.026 median in the control group. Both of these differences are statistically significant, providing preliminary evidence in support of ***H1***. Similarly, the median *DebtCost* of 0.024 in the treatment group is lower than the 0.026 median in the control group. In addition, notable variations between the two groups were observed in the control variables, including *Size*, *Lev*, *ROA*, and *Interest*.

< Insert Table 2>

4.2. Main Analysis

Table 3 presents the primary findings derived from the regression analysis. In column (1) of the regression analysis, Model (1) incorporates only the *Did* variable; the *Did* coefficient is -0.001, significant at the 5% level. Progressing to column (2), which presents refined outcomes after integrating control variables into Model (1), the *Did* coefficient remains at -0.001 but attains a higher level of significance at 1%. Although the magnitude of the coefficient appears numerically small, it represents an approximate 4% reduction relative to the sample mean of *DebtCost* of 0.025, which is economically meaningful. These results indicate that the implementation of the LCCP leads to a statistically and economically significant decrease in the cost of debt, thereby supporting ***H1***.

< Insert Table 3>

4.3. Robustness Test

4.3.1. Parallel Trends Test

A prerequisite for employing the DID methodology is the establishment of parallel trends between the treatment and control groups. Given that the third round of the LCCP within our sample selection period extended to 2020, three years after the implementation of the policy, we established a parallel trend test interval spanning three years before and three years following the policy's enactment. Consequently, the *DID* variable was incorporated into the regression analysis, covering the pre- and post-policy periods, specifically within the time frame of [-4, 3] years relative to the policy's implementation.

Figure 2 presents the results of the parallel trends test. Before the enactment of the LCCP, the regression coefficients of the *DID* variable, across various time points, exhibited confidence intervals that were not statistically significant. One year after the policy's implementation, the regression coefficients of the *DID* variable, at each time point, demonstrated a consistent downward trend, with confidence intervals excluding zero. Our results indicate that, after the implementation of the LCCP, the cost of debt in the pilot regions was significantly lower.

< Insert Figure 2>

4.3.2. Variable Substitution of the Cost of Debt

In a robustness test, we followed Pittman and Fortin (2004) and Bharath et al. (2008) to construct two new variables, *Debt_Cost1* and *Debt_Cost2*, to measure the cost of debt. Table 4 presents the results. Columns (1) and (2) display the outcomes about *Debt_Cost1*; both columns exhibit *Did* coefficients of -0.002, indicating statistical significance at the 5% level. Columns (3) and (4) display the *Debt_Cost2* results, showing that the *Did* coefficient is -0.003 and significant at the 5% level. These congruent results are consistent with ***H1***.

< Insert Table 4>

4.3.3. Placebo Test

To test the effectiveness of the LCCP on the cost of debt, we randomly selected one year before the pilot of the three treatment groups as the time point of impact and repeated the randomization process 100 times. The estimator is the placebo test regression coefficients, and the dots are the P-values of the placebo test *Did* coefficients. After randomization, the coefficients of *Did* skewed toward 0, which was smaller than the estimated true value of -0.001. This result implies the likelihood of measurement inaccuracies in the initial sample selection process as well as the potential influence of policy interventions, thereby highlighting the plausibility of errors and effects within the context of the study.

< Insert Figure 3>

4.3.4. Excluding Interference Factors

Concurrent environmental policies were excluded. When the LCCP was implemented, China introduced environmental regulations, such as the Carbon Trading Pilot (CTP) policy, the Smart City Pilot (SCP) policy, and the Green Credit Guidelines (GCG). To eliminate the potential effects of these policies and estimate the net effect of the LCCP, time indicator variables of the CTP, SCP, and GCG policies were introduced into Model (1). *CTP*, *SCP*, and *GCG* were defined as 1 for enterprises influenced by the CTP, SCP, and GCG policy and 0 otherwise.[①] We also incorporated additional variables to mitigate the impact of regional economic disparities across different areas and the variations among subsidiaries of different enterprises.

The results are presented in columns (1)-(5) of Table 5. In columns (1)-(4), the coefficients of CTP and SCP are not significant, indicating that the CTP and SCP policies have a small impact on the cost of debt. Enterprises are significantly affected by the GCG policy because the debt cost of GCG enterprises is significantly higher than that of non-GCG enterprises. In column (5), after incorporating additional control variables, the coefficient of -0.002 for *Did* is still significant at the 5% level. This suggests that, excluding interference factors, our original hypothesis still holds and the positive impact of the LCCP on the cost of debt remains robust.

< Insert Table 5>

4.3.5. Propensity Score Matching

The selection of LCCP pilot regions exhibits a degree of exogeneity; it remains based on voluntary applications, expert reviews, and regulatory approvals, potentially introducing selection bias. To address endogeneity concerns, we employ propensity score matching (PSM) while incorporating all control variables from Model (1).

The first two policy rounds are combined, with 2012 as the policy start year (Post = 1). Enterprises in these pilot areas form the treatment group (Treat = 1), and others constitute the

[①] We determined whether a listed company is affected by GCG by identifying whether that company's environmental and social risks are classified as A. Companies belonging to A fall into nine industries: nuclear power generation, hydroelectric power generation, water conservancy and inland waterways and ports engineering and construction, coal mining and washing, petroleum and natural gas mining, ferrous metal mining, nonferrous metal mining, nonmetallic mining, and other mining industries. These companies are affected by GCG, where the *GCG* variable equals 1.

control group (Treat = 0). Given the sample size disparity, we apply 1:1 nearest-neighbor matching without replacement and a caliper of 0.01. The matched sample contains 10,513 observations. Balance tests in Table 6 show that all covariate biases fall below 10% post-matching in Panel A, and no significant differences remain between groups in Panel B, indicating that it mitigates selection bias.

< Insert Table 6>

We then re-estimate Model (1) using the matched sample in a single-period DID design. As shown in Table 7, both the baseline DID and the PSM-DID estimates consistently show a coefficient of -0.002 for *DID*, significant at the 5% level, with or without control variables. These robust results support Hypothesis ***H1***.

< Insert Table 7>

4.3.6. Heterogeneity Treatment Effect Test

The LCCP was implemented in 2012 and 2017, expanding from 13 to 81 regions and creating overlapping treatment exposure within the sample. To evaluate potential bias due to variation in treatment timing, we applied the Goodman-Bacon (2021) decomposition for the staggered DID model. In this framework, the estimated policy effect from the baseline regression represents a weighted average of multiple 2×2 DID comparisons. Certain pair-wise estimates using already-treated LCCP regions as controls may carry negative weights, which can bias the baseline estimate. Accordingly, we focused on group-type comparisons A, B, and C as no units were treated throughout the entire study period.

As presented in Table 8, Panel A, Type B employs already-treated units as controls, a methodologically suboptimal approach that may introduce bias into the DID estimate. In contrast, Types A and C utilize never-treated units, offering a more reliable counterfactual. Collectively, Types A and C comprise 81.5% of the weighting, whereas Type B accounts for the remaining 19.5%. After excluding Type B, we find that the combined estimate for Types A and C continues to show a positive effect.

Second, the staggered DID design can introduce bias into traditional two-way fixed effects models (Chaisemartin and Haultfoeuille, 2020). Under the overlapping implementation of the LCCP, the estimated effect represents a weighted sum of treatment effects across multiple subgroups. To address this, we additionally applied the Callaway and Sant'Anna (2021) estimator, which uses never-treated units as the control group in a doubly robust framework. Using the "csdid" command, we recomputed the average treatment effect on the treated (ATT). As reported in Panel B of Table 8, the ATT is -0.002 and significant at the 1% level, supporting the robustness of our conclusions even after accounting for treatment effect heterogeneity.

< Insert Table 8>

4.3.7. Spillover Effect Test

The LCCP exerts a more pronounced impact on enterprises in the manufacturing and supply sectors, which are typically characterized by multi-plant operations and greater exposure to environmental regulation. To examine whether the policy effect spills over to other industries, we reclassify the sample into two groups: manufacturing and supply industries, and all others. We then re-estimate the model.

The results are presented in Table 9. Column (1) shows the results of the manufacturing and supply industries. The coefficient of *Did* is -0.001, which is significant at the 5% level. Column (2) presents the results of other industries. The coefficient of *Did* is -0.002, which is significant at the 1% level. The intergroup comparison of coefficients reveals no discernible disparity between the two groups. The implementation of LCCP exerts a significant influence on the cost of debt incurred by enterprises of all types within the pilot region.

< Insert Table 9>

5. Further Analysis

Based on the causal effect of the LCCP on reducing corporate debt cost, this section delves deeper into two critical dimensions to enrich our understanding of the policy's impact. First, we investigate the underlying mechanisms through which the LCCP influences debt financing costs, testing whether the effect operates primarily via enhanced corporate ESG performance and reduced information asymmetry. Second, we examine heterogeneous treatment effects across different firm and regional characteristics to identify under which conditions the policy is most potent. While the staggered DID design isolates the average treatment effect, this cross-sectional analysis reveals important boundary conditions and practical nuances, such as varying agency costs and regional disparities that shape the policy's real-world effectiveness. By integrating these complementary studies into this section, we can comprehensively demonstrate how LCCP affects a company's financial results.

5.1 Mechanism Test

5.1.1 ESG Performance Mechanism

The improvement of ESG performance indicates the continuous improvement and enhancement of the enterprise's sustainability, and the cost of debt is lower when the performance is better. As the LCCP is a comprehensive environmental policy, enterprises will adjust their sustainable development strategies in response to the policy to improve their ESG performance. Studies found that higher ESG performance reduces the cost of debt (Ghoul et al., 2017). Following Nitzl et al. (2016), we constructed Models (2) and (3) to test the impact of ESG:

$$LnESG_{it} = \beta_0 + \beta_1 Did_{it} + Control\,Variables_{it} + \varepsilon_{it} \tag{2}$$

$$DebtCost_{it} = \beta_0 + \beta_1 Did_{it} + \beta_2 lnESG_{it} + Control\,Varialbes_{it} + \varepsilon_{it} \tag{3}$$

The dependent variable in Model (2), enterprise ESG performance (ESG), is collected from the CSI ESG index. The results of the ESG performance mechanism are presented in Table 10. In column (1), the coefficient of *Did* is -0.001, which is significant at the 1% level. In column (2), the coefficient of *Did* is -0.015, which is significant at the 1% level. In column (3), the coefficient of *Did* is -0.001, and that of *lnESG* is -0.002, which are significant at the 1% and 10% levels, respectively. We performed the Sobel test on the regression, where the Z value is -2.327, and the P value is 0.022.[②] The results indicate that the LCCP improves enterprises' ESG performance, which reduces the cost of debt.

< Insert Table 10>

5.1.2. Information Asymmetry Mechanism

In the past, enterprises were unwilling to disclose carbon information; under the influence of the LCCP, the volume of carbon-related information disclosed by enterprises is anticipated to escalate. The carbon-related information brought about by the enterprise's production activities will enhance the transparency of the enterprise's information disclosure. To verify whether the LCCP can enhance enterprises' information transparency and reduce the

[②] This is a simple test statistic proposed by Sobel (1982). The Sobel test is utilized to examine the hypothesis in which the relationship between the independent (X) and dependent (Y) variables is mediated and affected by a third variable (M); that is, X and Y have an indirect relationship through M.

cost of debt, we used a proxy variable with information asymmetry (*FDISP*) as a moderating factor in Models (2) and (3).

Table 11 presents the results of the information asymmetry mechanism. In column (1), the coefficient of *Did* is -0.001, which is significant at the 1% level. In column (2), the coefficient of *Did* is -0.291, which is significant at the 1% level. In column (3), the coefficient of *Did* is -0.001, and that of *FDISP* is 0.000; both are significant at the 1% level. We performed the Sobel test on the regression, where the Z value is -2.214, and the P value is 0.019. The results indicate that the LCCP reduces enterprises' information asymmetry and eventually reduces the cost of debt.

< Insert Table 11>

5.2 Cross-sectional Analysis

5.2.1. Agency Cost Differences

In environmental governance, managers often violate the interests of shareholders through the waste of resources, overinvestment, excessive emissions, and misappropriation of environmental funds. These behaviors will cause the agency's costs to rise. Managers' high agency costs send negative signals to the capital market when enterprises carry out debt financing, thereby leading them to encounter higher financing barriers. To verify whether the LCCP can reduce the impact of agency cost on an enterprise's cost of debt, we constructed Model (4).

$$DebtCost_{it} = \beta_0 + \beta 1 Did_{it} * HAC + \beta_2 Did_{it} + \beta_3 HAC + Control\,Variables_{it} + \varepsilon_{it} \quad (4)$$

HAC represents the high agency cost dummy variable. If the agency cost for the enterprise is greater than the average agency cost of the sample, it is assigned a value of 1; otherwise, it is assigned a value of 0.

Table 12 presents the regression result of Model (4). In column (1), the coefficient of *Did*HAC* is -0.001, which is significant at the 5% level. The coefficient of *Did* is -0.001, which is significant at the 10% level. The coefficient of *HAC* is 0.002, which is significant at the 1% level. The results show that the higher the agency cost, the greater the reduction in corporate debt costs caused by the implementation of the LCCP policy, and the more obvious the effect.

< Insert Table 12>

5.2.2 Regional Differences

A notable variation exists in the long-term economic progression across China's diverse regions. Traditional industries still dominate the industrial environment in the country's western region. The central and western regions lag behind their eastern counterparts in terms of their prowess in green innovation. In the realm of enterprise financing, more investors than ever are now focusing on enterprises' abilities to grow and develop sustainably over time. The disparity in sustainable development capabilities between China's eastern and western regions may motivate investors to delve into the influence of regional factors on the cost of debt experienced by enterprises.

We used a regional variable (*Region*) as an indicator variable. When the company was situated in the eastern regions, the *Region* was set to 1; otherwise, it was set to 0.[3] We used

[3] Excluding the Hong Kong Special Administrative Region, Macao Special Administrative Region, and Taiwan Province, the eastern region comprises Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Guangdong, and Hainan. The central and western regions consist of Jilin, Heilongjiang, Shanxi, Inner Mongolia, Henan, Hubei, Hunan, Guangxi Zhuang Autonomous Region, Chongqing, Sichuan, Guizhou, Yunnan, Tibet Autonomous Region, Shaanxi, Gansu, Qinghai, Ningxia Hui Autonomous Region, and Xinjiang Uyghur Autonomous Region.

this variable as a moderating factor in Model (4). Column (1) of Table 13 presents the result. The coefficient of *Did*Region* is -0.002, which is significant at the 5% level; the coefficient of *Did* is 0.000, which is insignificant. The results show that under the implementation of the LCCP policy, the debt cost reduction of enterprises in the eastern region is significantly higher than that of enterprises in the central and western regions. This is mainly due to the greater financial resources and stronger support for the sustainable development of enterprises in the eastern region.

< Insert Table 13>

6. Conclusions

The LCCP has emerged as a core policy instrument aimed at bolstering green innovation endeavors, accelerating the green transformation of enterprises, and executing the "dual-carbon" target strategy. This study analyzed how the LCCP affects enterprises' cost of debt by studying Chinese A-share listed enterprises and whether it plays a substantial role in mitigating their cost of debt. The results indicate that the LCCP reduces the cost of debt and boosts enterprises' low-carbon development and green transformation. Our results support the government's efforts to implement and promote the LCCP among enterprises in pilot regions.

We tested the mechanism by which the LCCP reduces an enterprise's cost of debt through two channels: its ESG performance and its information transparency. We found that the LCCP can improve both channels, thereby decreasing the cost of debt. We further tested whether the impact of the LCCP is influenced by enterprises' agency costs and regional differences. It indicates the LCCP's ability to reduce the cost of debt is particularly pronounced for firms with higher agency costs and those located in China's eastern regions. The cost of debt is higher in central and western China, where economic development is rather slow. These enterprises are often overlooked and at a disadvantage, and face difficulties in securing external funding. They need financial assistance from the government for their green transition.

The LCCP, as a comprehensive and far-reaching environmental regulation policy with an early onset, serves as a quasi-natural experiment, facilitating the examination of the influence of China's environmental regulatory policy on enterprises. As China's pioneering policy for exploring low-carbon production and development, the LCCP has enhanced the environmental improvement of the pilot regions and promoted the development of enterprises in the pilot regions. The outcomes of the LCCP can be extended beyond China's borders, offering insights applicable to other developing countries in their development trajectories. The government(s) should continue to promote environmental regulations, which will help enterprises raise awareness of sustainable development, increase their green production capabilities, and accelerate their industrial transformation and development. They need to design climate policies that actively engage the enterprise and the financial system to support a sustainable economic transformation. Although the cost of debt for some enterprises, especially high carbon emission enterprises, is higher, the good climate policies can help enterprises to carry out green transformation, and vigorously enhance their green capabilities, which will improve their ESG performance, reduce information asymmetry, and thus lower their debt costs.

This study acknowledges several limitations. First, despite our empirical design, potential policy leakage or spillover effects to neighboring non-pilot regions through supply chains cannot be fully ruled out, which may attenuate the estimated treatment effect. Second, the focus on A-share listed firms limits the generalizability of findings to smaller enterprises. Future research using more granular spatial data and extending the time frame would help address these caveats.

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Appendix. Variable Definitions

CoD

DebtCost: Following Minnis (2011), we used the net finance cost ratio (i.e., net finance cost divided by the total liabilities of the enterprise) as a measure of CoD. We used "interest expense plus fee expense and other finance costs" as the net finance cost, because the enterprises may also pay fees and other expenses in addition to interest expense when using debt financing.

Low-Carbon City Pilot Policy

Did: It is a dummy variable. *Did=Treat*Post*. If *Did* equals 1, it means that the city in which the sample year is located has implemented a Low Carbon City Policy. If *Did* equals 0, it means that this policy was not implemented. We built a treatment group and a control group. If City *I* were implemented as a Low-Carbon City Pilot Policy, then we would treat the company that registered in this city as a treatment group (*Treat*=1). If this company is not in the low-carbon pilot city, it is a control group (*Treat* =0). *Post* is a dummy variable for policy implementation. Since the Low-Carbon City Pilot Policy was implemented in 2010, 2012, and 2017, cities from the first batch of low-carbon city pilots in 2010 are considered to have started in 2011 (i.e., *Post* is 1 for 2011 and later, 0 otherwise); cities from the second batch in 2012 are considered to have started in 2013 (i.e., *Post* is 1 for 2013 and later, 0 otherwise), and cities from the third batch in 2017 are considered to have started in 2017 (i.e., *Post* is 1 for 2018 and later, 0 otherwise).

Control Variables

State: If the enterprise is state-controlled, it is 1, otherwise itis 0.
Big_N: If the auditors of the enterprise are from the top 10 Chinese domestic accounting firms and the top 4 international accounting firms,itis1, otherwise itis 0.
Size: Enterprise size, which equals the natural logarithm of the total assets.
Lev: Leverage ratio, which equals total liabilities divided by total assets.
ROA: Return on assets, which equals net income divided by total assets.
Growth: Growth rate of sales, which equals the current year's revenue minus last year's revenue divided by last year's revenue.
PPE: Fixed asset ratio, which equals net fixed assets divided by total assets.
Interest: EBITDA divided by interest expense.
FCF: Operating net cash flow activities divided by total assets.
Loss: If the firm's net profit is negative, it is 1, otherwise it is 0.
Top1: Ownership concentration, which equals the shareholding ratio of the largest shareholder.
Duality: If the chairman of the board and the general manager are the same people, it is 1, otherwise it is 0.
Indep: Number of independent directors divided by the total number of board members.

Robust Variables

Debt_Cost1: Average interest expense divided by the sum of long and short-term debt. Short-term liabilities are short-term borrowings in the balance sheet, and long-term liabilities include long-term borrowings due within one-year, long-term loans, bonds payable, long-term payables, and other long-term liabilities.
Debt_Cost2: Average interest expense divided by the sum of interest-bearing debt at the beginning of

the year and interest-bearing debt at the end of the year. Interest-bearing liabilities include short-term borrowings, long-term borrowings, long-term liabilities due in one year, and bonds payable.

CTP: Carbon Trading Pilot Policy dummy variable. It is defined as *CTP*. If City *i* was implemented as Carbon Trading Pilot Policy, then we treat the company who register in this city as the treatment group (*CTPTreat*=1). *CTPPost* is a dummy variable for policy implementation. Since the Carbon Trading Pilot Policy was implemented in 2011 (i.e., *CTPPost* is 1 for 2011 and later, 0 otherwise) and 2013 (i.e., *Post* is 1 for 2013 and later, 0 otherwise). *CTP*= (*CTPTreat***CTP Post*). If *CTP* equals 1, it means that the city in which the sample year is located has implemented a Carbon Trading Pilot Policy. If *CTP* equals 0, it means that this policy was not implemented.

The Carbon Trading Pilot Policy (CTP) was introduced in October 2011. When energy-using units' original carbon emission allowances are insufficient, they can acquire the necessary allowances to ensure that the cumulative carbon emissions across the entire vast region remain within manageable limits.

SCP: Smart City Pilot Policy dummy variable. It is defined as *SCP*, If City *i* was implemented as Smart City Pilot Policy, then we treat the company who register in this city as the treatment group (*SCP Treat*=1). *SCPPost* is a dummy variable for policy implementation. Since the Smart City Pilot Policy was implemented in 2013 (i.e., *SCPPost* is 1 for 2013 and later, 0 otherwise) and 2015 (i.e., *Post* is 1 for 2015 and later, 0 otherwise). *SCP*=(*SCPTreat***SCPPost*). If *SCP* equals 1, it means that the city in which the sample year is located has implemented a Smart City Pilot Policy. If *SCP* equals 0, it means that this policy was not implemented.

The Smart City Pilot Policy (SCP) was introduced on December 5, 2012. Cities with intelligent sensors can create an Internet of Things, optimizing pollution control methods and technologies for enterprises.

GCG: Green Credit Guidelines Policy dummy variable. If company environmental and social risks are classified as A, we treat the company as a treatment group (*GCGTreat*=1). *GCGPost* is a dummy variable for policy implementation. Since the Green Credit Guidelines were implemented in 2012 (i.e., *GCG Post* is 1 for 2012 and later, 0 otherwise). *GCG*=(*GCG Treat***GCG Post*). If *GCG* equals 1, it means that the company in the sample year has implemented Green Credit Guidelines. If *GCG* equals 0, it means that this policy was not implemented. The industry to which the company belongs in "A" includes nine industries, including nuclear power generation, hydroelectric power generation, water conservancy and inland waterways and ports engineering and construction, coal mining and washing, petroleum and natural gas mining, ferrous metal mining, nonferrous metal mining, nonmetallic mining, and other mining industries.

The Green Credit Guidelines (GCG) issued on February 24, 2012, required financial institutions to promote green credit and support green, low-carbon, and circular economies.

lnFDI: Foreign Direct Investment, which equals the natural logarithm of the FDI.

lnGDP: Gross Domestic Product of the company registered in this city, which equals the natural logarithm of the GDP.

PI: The primary sector of industry of the company registered in this city, which equals the share of the primary sector of industry in GDP.

SI: The second sector of industry of the company registered in this city, which equals the share of the Second sector of industry in GDP.

Subs: The subsidiaries of the enterprise, which equals the natural logarithm of the number of subsidiaries plus 1.

Mechanism Variables

lnESG: Enterprises ESG performance, which equals the natural logarithm of the CSI ESG Score. The CSI ESG ratings encompass a broader spectrum of China's A-share market, utilizing three core metrics, 14 subordinate indicators, 26 tertiary indices, and more than 130 foundational data points, providing a comprehensive assessment. The bottom-up indexes are summed up according to the industry weight matrix to get the ESG scores of enterprises and the final AAA-C rating of nine grades. AAA is 9 points, AA is 8 points, and C is 1 point. The CSI ESG ratings are rated once a quarter, so the ESG scores of enterprises are summed up every quarter to determine the average, and the logarithmic processing of the scores to get the *lnESG* variable.

FDISP: Analyst forecast divergence measure, which equals the analyst profit forecast (FEPS) divided by the mean analyst profit forecast (MEPS). FEPS is the analyst profit forecast, MEPS is the analyst profit forecast average, and FDISP is the analyst forecast EPS standard deviation divided by the absolute value of the actual earnings per share. The higher the transparency of enterprise information, the lower the divergence of analyst forecasts is. *FDISP* is calculated as follows:

$$FDISP_{it}=\frac{Std(FEPS_{it})}{Abs(MEPS_{it})}$$

Cross-sectional Variables

HAC: High agent cost dummy variable. If the agent cost for the enterprise is greater than the average agent cost for all samples, it is assigned a value of 1; otherwise, it is assigned a value of 0. The enterprise agency cost (AC) is calculated as the enterprise's other receivables divided by total assets.

Region: Regional dummy variable. Excluding the Hong Kong Special Administrative Region, Macao Special Administrative Region, and Taiwan Province, the eastern region comprises Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Guangdong, and Hainan. The central and western regions consist of Jilin, Heilongjiang, Shanxi, Inner Mongolia, Henan, Hubei, Hunan, Guangxi Zhuang Autonomous Region, Chongqing, Sichuan, Guizhou, Yunnan, Tibet Autonomous Region, Shaanxi, Gansu, Qinghai, Ningxia Hui Autonomous Region, and Xinjiang Uyghur Autonomous Region. If an enterprise is located in the eastern regions, the *Region* is defined as 1; otherwise, it is 0.

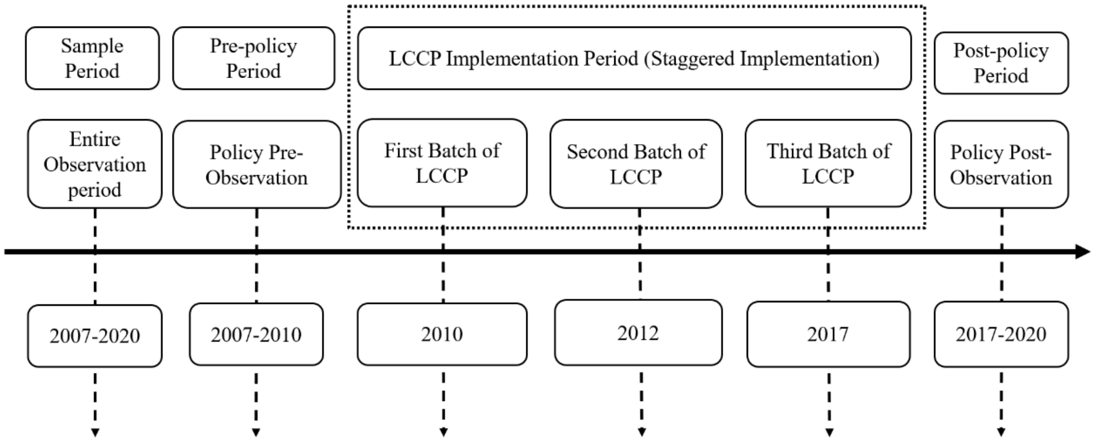

Figure 1. LCCP Timeline

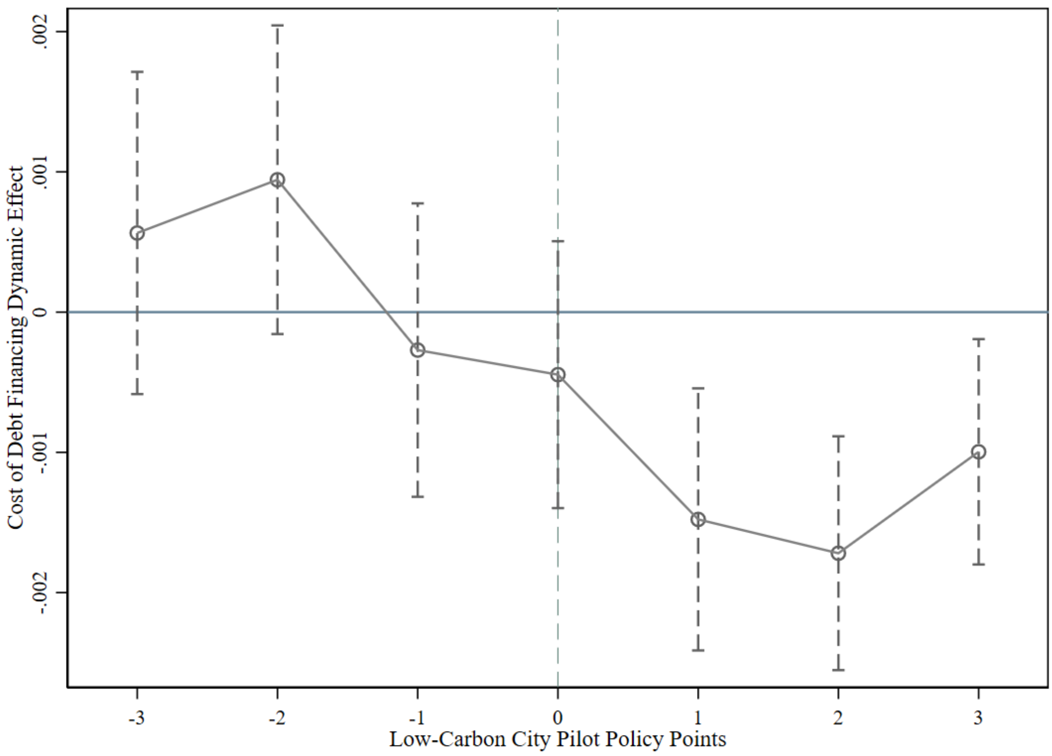

Figure 2. Parallel Trends Test

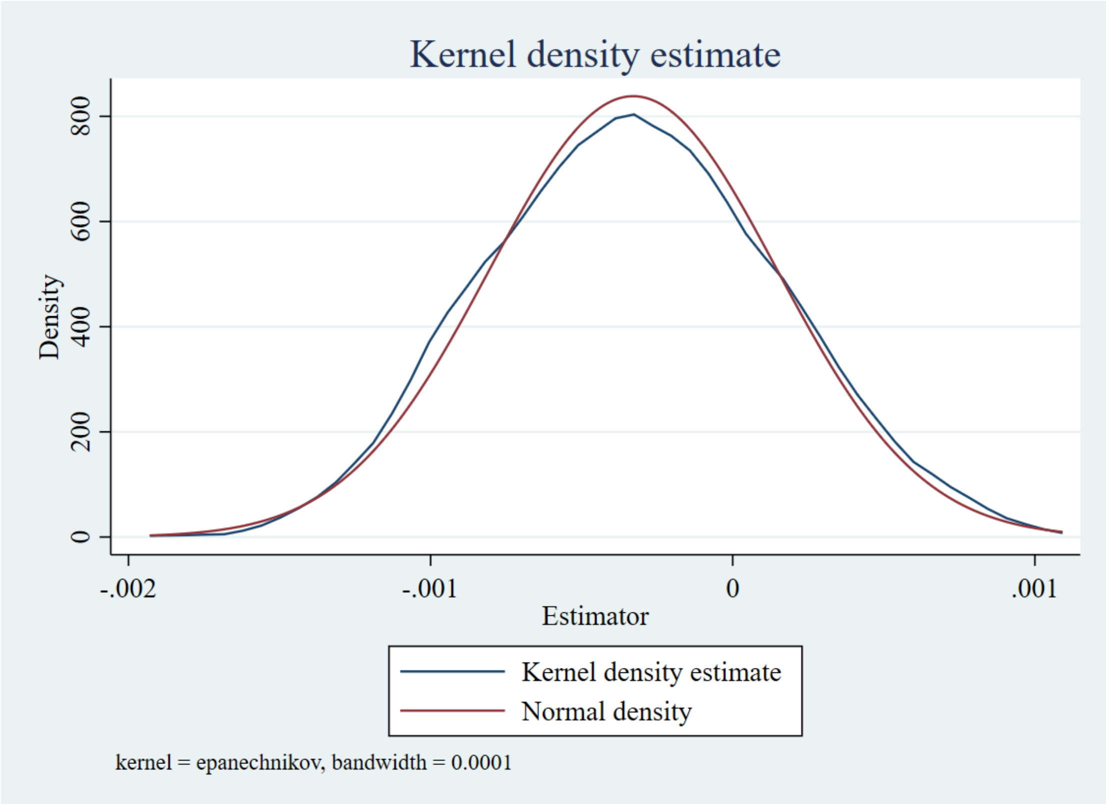

Figure 3. Random Treatment Group Time Placebo Test

Table 1. Timing of Low-Carbon City Pilot Policy

Time	Pilot areas (provinces, cities, districts)
First pilot low-carbon cities (start from 2010)	Guangdong, Liaoning, Hubei, Shaanxi, Yunnan, Tianjin, Hangzhou, Shenzhen, Xiamen, Baoding, Nanchang, Chongqing, Guiyang
Second pilot low-carbon cities (start from 2012)	Hainan, Beijing, Shanghai, Shijiazhuang, Qinhuangdao, Suzhou, Huaian, Zhenjiang, Ningbo, Wenzhou, Nanping, Qingdao, Jiyuan, Guangzhou, Jincheng, Jilin, Daxing'anling, Chizhou, Jingdezhen, Ganzhou, Wuhan, Hulunbeier, Guilin, Guangyuan, Zunyi, Kunming, Yan'an, Jinchang, Urumqi
Third pilot low-carbon cities (start from 2017)	Nanjing, Changzhou, Jiaxing, Jinhua, Quzhou, Sanming, Jinan, Yantai, Weifang, Zhongshan, Shenyang, Dalian, Chaoyang, Sanya, Qiongzhong Li and Miao Autonomous County, Sunken County, Hefei, Huaibei, Huangshan, Lu'an, Xuancheng, Gongqingcheng, Ji'an, Fuzhou, Changyang Tujia Autonomous County, Changsha, Zhuzhou, Xiangtan, Chenzhou, Wuhai, Liuzhou, Chengdu, Yuxi, Pu'er, Lhasa, Ankang, Lanzhou, Dunhuang, Xining, Yinchuan, Wuzhong, Changji, Yining, Hotan, Xinjiang Construction Corps

Notes: We report three batches of Low-Carbon City Pilot Policy. Cities belonging to Guangdong province, Liaoning province, Hubei province, Shaanxi province, Yunnan province and Hainan province are all considered as pilot cities. If a subordinate area is a low-carbon pilot city, its superior city is also considered as pilot cities.

Table 2. Descriptive Statistics

Variable	Full Sample				Treatment (Treat=1)			Control (Treat=0)		
	N	Mean	Media	SD	N	Mean	Media	N	Mean	Media
DebtCost	22,733	0.025	0.024	0.015	15,933	0.025	0.024	6,800	0.027***	0.026***
Did	22,733	0.490	0.000	0.500	15,933	0.699	1.000	6,800	0.000***	0.000***
State	22,733	0.434	0.000	0.496	15,933	0.448	0.000	6,800	0.401***	0.000***
Big_N	22,733	0.512	1.000	0.500	15,933	0.524	1.000	6,800	0.484***	0.000
Size	22,733	22.32	22.15	1.300	15,933	22.37	22.17	6,800	22.22***	22.09***
Lev	22,733	0.499	0.496	0.181	15,933	0.503	0.500	6,800	0.488***	0.487***
ROA	22,733	0.026	0.029	0.063	15,933	0.025	0.029	6,800	0.026	0.029
Growth	22,733	0.175	0.106	0.428	15,933	0.179	0.107	6,800	0.165**	0.101
PPE	22,733	0.408	0.403	0.180	15,933	0.397	0.389	6,800	0.434***	0.430***
Interest	22,733	18.14	4.639	55.92	15,933	18.76	4.784	6,800	16.66***	4.324***
FCF	22,733	0.042	0.043	0.069	15,933	0.041	0.042	6,800	0.046***	0.045***
Loss	22,733	0.121	0.000	0.326	15,933	0.120	0.000	6,800	0.124	0.000
Top1	22,733	34.16	32.02	14.80	15,933	34.38	32.16	6,800	33.64***	31.61
Duality	22,733	0.227	0.000	0.419	15,933	0.230	0.000	6,800	0.220	0.000
Indep	22,733	37.34	33.33	5.375	15,933	37.48	33.33	6,800	37.00***	33.33***

Notes: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, similarly hereinafter.

Table 3. Baseline Regression

	(1) DebtCost	(2) DebtCost
Did	-0.001**	-0.001***
	(-2.57)	(-2.70)
State		0.001
		(1.15)
Big_N		0.001**
		(2.48)
Size		-0.000
		(-1.14)
Lev		0.002
		(1.52)
ROA		-0.019***
		(-6.50)
Growth		-0.001***
		(-5.21)
PPE		0.006***
		(3.47)
Interest		-0.000***
		(-19.87)
FCF		0.022***
		(12.81)
Loss		0.001***
		(2.64)
Top1		-0.000*
		(-1.89)
Duality		0.000
		(0.35)
Indep		0.000
		(0.41)
Constant	0.023***	0.029***
	(61.68)	(3.56)
Year	Yes	Yes
Firm	Yes	Yes
Cluster	Yes	Yes
N	22,733	22,733
R^2	0.090	0.150
Adj. R^2	0.089	0.149

Notes: We report t-statistics in parentheses below fully standardized coefficients. Standard errors are clustered at the firm level. Firm fixed effect and year fixed effect are both controlled. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Variable substitution

	(1) Debt_Cost1	(2) Debt_Cost1	(3) Debt_Cost2	(4) Debt_Cost2
Did	-0.002**	-0.002**	-0.003**	-0.003**
	(-1.98)	(-2.04)	(-2.05)	(-2.10)
State		0.003		0.003
		(1.31)		(1.44)
Big_N		0.002**		0.002*
		(2.57)		(1.73)
Size		-0.004***		-0.005***
		(-5.34)		(-5.20)
Lev		-0.003		-0.008*
		(-0.96)		(-1.86)
ROA		-0.023***		-0.020**
		(-3.48)		(-2.52)
Growth		0.004***		0.006***
		(7.14)		(7.83)
PPE		-0.002		-0.005
		(-0.69)		(-1.32)
Interest		-0.000***		-0.000***
		(-7.97)		(-5.72)
FCF		0.028***		0.031***
		(7.10)		(6.87)
Loss		0.002***		0.004***
		(2.77)		(3.68)
Top1		-0.000**		-0.000***
		(-2.41)		(-2.92)
Duality		0.001		0.001
		(0.74)		(0.74)
Indep		0.000		0.000
		(0.61)		(0.97)
Constant	0.052***	0.144***	0.054***	0.161***
	(43.75)	(8.69)	(41.40)	(8.36)
Year	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
N	22,275	22,275	22,275	22,275
R2	0.062	0.086	0.057	0.078
Adj. R2	0.062	0.085	0.056	0.077

Notes: We report t-statistics in parentheses below fully standardized coefficients. Standard errors are clustered at the firm level. Firm fixed effect and year fixed effect are both controlled. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Excluding Interference

	(1) DebtCost	(2) DebtCost	(3) DebtCost	(4) DebtCost	(5) DebtCost
Did	-0.001**	-0.001***	-0.001***	-0.001**	-0.002***
	(-2.27)	(-2.81)	(-2.68)	(-2.33)	(-3.26)
CTP	-0.001			-0.001	
	(-1.33)			(-1.52)	
SCP		0.000		0.001	
		(0.82)		(0.93)	
GCG			0.003*	0.003	
			(1.70)	(1.64)	
State	0.001	0.001	0.001	0.001	0.001
	(1.15)	(1.14)	(1.17)	(1.17)	(0.81)
Big_N	0.001**	0.001**	0.001**	0.001**	0.001***
	(2.49)	(2.52)	(2.50)	(2.56)	(3.39)
Size	-0.000	-0.000	-0.000	-0.000	-0.001***
	(-1.15)	(-1.14)	(-1.19)	(-1.20)	(-2.75)
Lev	0.002	0.002	0.002	0.002	0.001
	(1.54)	(1.52)	(1.53)	(1.56)	(0.83)
ROA	-0.019***	-0.019***	-0.018***	-0.018***	-0.018***
	(-6.52)	(-6.51)	(-6.38)	(-6.41)	(-5.75)
Growth	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-5.21)	(-5.19)	(-5.17)	(-5.16)	(-3.77)
PPE	0.006***	0.006***	0.006***	0.006***	0.005***
	(3.50)	(3.46)	(3.50)	(3.51)	(2.82)
Interest	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-19.84)	(-19.89)	(-19.88)	(-19.88)	(-17.17)
FCF	0.022***	0.022***	0.023***	0.023***	0.021***
	(12.81)	(12.81)	(12.88)	(12.86)	(10.99)
Loss	0.001***	0.001***	0.001***	0.001***	0.001**
	(2.61)	(2.65)	(2.74)	(2.70)	(2.47)
Top1	-0.000*	-0.000*	-0.000*	-0.000**	-0.000
	(-1.92)	(-1.93)	(-1.92)	(-1.98)	(-1.43)
Duality	0.000	0.000	0.000	0.000	0.000
	(0.36)	(0.36)	(0.38)	(0.40)	(0.32)
Indep	0.000	0.000	0.000	0.000	0.000
	(0.41)	(0.41)	(0.42)	(0.43)	(0.33)
lnGDP					-0.002
					(-1.35)
lnFDI					-0.000
					(-0.48)
PI					0.000
					(0.02)
SI					0.000***
					(2.62)
Subs					0.002***
					(4.23)
Constant	0.029***	0.029***	0.030***	0.030***	0.002***
	(3.57)	(3.57)	(3.61)	(3.64)	(4.23)
Year	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes
N	22,733	22,733	22,733	22,733	18,692
R^2	0.150	0.150	0.150	0.151	0.150

Adj. R^2	0.149	0.149	0.149	0.150	0.149

Notes: We report t-statistics in parentheses below fully standardized coefficients. Standard errors are clustered at firm level. Firm fixed effect and year fixed effect are both controlled. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Equilibrium test after PSM

Panel A. Matched results

Variables	Mach	Mean		S.B (%)	Deviation reduction ratio (%)	T-test	
		Treatment	Control			T	P>|t|
State	Unmatched	0.529	0.488	8.0	88.1	4.62	0.000
	Matched	0.498	0.503	-1.0		-0.51	0.611
Big_N	Unmatched	0.479	0.433	9.2	69.8	5.27	0.000
	Matched	0.433	0.447	-2.8		-1.48	0.140
Size	Unmatched	22.26	22.07	15.3	81.8	8.71	0.000
	Matched	22.07	22.11	-2.9		-1.59	0.112
Lev	Unmatched	0.515	0.510	2.7	44.7	1.56	0.119
	Matched	0.507	0.510	-1.5		-0.80	0.423
ROA	Unmatched	0.030	0.026	6.1	87.1	3.53	0.000
	Matched	0.028	0.028	0.8		0.42	0.671
Growth	Unmatched	0.199	0.168	7.1	98.4	4.04	0.000
	Matched	0.173	0.174	-0.1		-0.06	0.950
PPE	Unmatched	0.429	0.459	-17.3	86.1	-9.90	0.000
	Matched	0.455	0.450	2.4		1.30	0.194
Interest	Unmatched	17.62	14.22	6.9	89.5	3.92	0.000
	Matched	15.14	14.78	0.7		0.42	0.678
FCF	Unmatched	0.039	0.042	-5.0	80.3	-2.87	0.004
	Matched	0.042	0.041	1.0		0.52	0.603
Loss	Unmatched	0.101	0.122	-6.5	99.5	-3.75	0.000
	Matched	0.112	0.112	0.0		0.02	0.986
Top1	Unmatched	35.76	34.80	6.4	68.7	3.68	0.000
	Matched	34.83	35.13	-2.0		-1.08	0.281
Duality	Unmatched	0.193	0.186	1.8	95.9	1.04	0.297
	Matched	0.190	0.190	0.1		0.04	0.968
Indep	Unmatched	37.24	36.65	11.4	83.7	6.52	0.000
	Matched	36.65	36.74	-1.9		-1.04	0.301

Panel B. Comparison of pre-match and post-match samples

Sample	Pseudo R2	LR chi2	p > chi2	Mean value of deviation	Median deviation
Unmatched	0.016	292.40	0.000	8.0	6.9
Matched	0.001	8.98	0.775	1.3	1.0

Table 7. Single-period DID and PSM-DID

	(1) DebtCost	(2) DebtCost	(3) DebtCost	(4) DebtCost
Did	-0.001**	-0.001**	-0.002**	-0.002**
	(-2.13)	(-2.12)	(-1.97)	(-2.03)
State		0.001		0.001
		(0.43)		(0.36)
Big_N		0.003***		0.003***
		(5.49)		(4.88)
Size		-0.002***		-0.002***
		(-2.80)		(-3.08)
Lev		-0.005**		-0.006**
		(-2.53)		(-2.50)
ROA		-0.021***		-0.022***
		(-4.76)		(-4.29)
Growth		0.000		-0.000
		(0.41)		(-0.64)
PPE		0.009***		0.008***
		(4.17)		(3.58)
Interest		-0.000***		-0.000***
		(-14.41)		(-12.09)
FCF		0.022***		0.025***
		(9.94)		(9.88)
Loss		0.001		0.000
		(1.42)		(0.50)
Top1		-0.000		-0.000
		(-1.23)		(-0.87)
Duality		0.001		0.001
		(1.16)		(1.12)
Indep		0.000		0.000
		(0.72)		(1.16)
Constant	0.023***	0.054***	0.024***	0.061***
	(46.08)	(4.63)	(42.71)	(4.72)
Year	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
N	13,403	13,403	10,513	10,513
R^2	0.128	0.176	0.130	0.178
adj. R^2	0.128	0.175	0.129	0.176

Notes: We report t-statistics in parentheses below fully standardized coefficients. Standard errors are clustered at the firm level. Firm fixed effect and year fixed effect are both controlled. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Heterogeneity Treatment Effect Test

Panel A. Bacon Decomposition

Category	DD Comparison		Weight	Avg DD Est
	Treatment	Comparison		
A	Earlier	Later	0.173	-0.002
B	Later	Earlier	0.195	-0.001
C	Treated	Never Treated	0.632	-0.003

Panel B. double-robust estimation

	Coef.	Z	P > |Z|
ATT	-0.002	-3.25	0.001

Table 9. Spillover Effect Test

	(1) DebtCost M&S Industry	(2) DebtCost Other Industry
Did	-0.001**	-0.002***
	(-2.14)	(-2.67)
State	0.000	0.002
	(0.26)	(1.17)
Big_N	0.001*	0.001*
	(1.67)	(1.79)
Size	0.000	-0.002**
	(0.54)	(-2.46)
Lev	0.003*	0.002
	(1.75)	(0.74)
ROA	-0.020***	-0.011**
	(-5.87)	(-2.15)
Growth	-0.002***	-0.001**
	(-5.02)	(-2.35)
PPE	0.012***	0.001
	(5.81)	(0.27)
Interest	-0.000***	-0.000***
	(-16.18)	(-11.68)
FCF	0.025***	0.019***
	(10.57)	(7.04)
Loss	0.001*	0.001
	(1.79)	(1.62)
Top1	-0.000	-0.000**
	(-1.09)	(-2.29)
Duality	0.000	-0.000
	(0.86)	(-0.66)
Indep	-0.000	0.000
	(-0.26)	(0.96)
Constant	0.014	0.054***
	(1.40)	(3.93)
Year	Yes	Yes
Firm	Yes	Yes
Cluster	Yes	Yes
Group Difference	0.73	
N	14,853	7,880
R^2	0.179	0.129
adj. R^2	0.177	0.126

Notes: We report t-statistics in parentheses below fully standardized coefficients. Standard errors are clustered at the firm level. Firm fixed effect and year fixed effect are both controlled. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10. ESG performance mechanism

	(1) DebtCost	(2) lnESG	(3) DebtCost
Did	-0.001***	0.015***	-0.001***
	(-3.00)	(3.13)	(-2.92)
lnESG			-0.002*
			(-1.96)
State	0.001	-0.005	0.001
	(0.87)	(-0.49)	(0.86)
Big_N	0.000	0.009**	0.000
	(0.75)	(2.56)	(0.80)
Size	-0.001	0.027***	-0.001
	(-1.35)	(7.34)	(-1.22)
Lev	0.003*	-0.095***	0.003
	(1.75)	(-6.55)	(1.63)
ROA	-0.018***	0.099***	-0.018***
	(-6.43)	(3.17)	(-6.36)
Growth	-0.001***	-0.005**	-0.001***
	(-5.29)	(-2.31)	(-5.32)
PPE	0.006***	0.040***	0.006***
	(3.45)	(2.99)	(3.49)
Interest	-0.000***	0.000	-0.000***
	(-19.20)	(0.54)	(-19.17)
FCF	0.024***	-0.049***	0.023***
	(13.30)	(-3.00)	(13.25)
Loss	0.001***	-0.004	0.001***
	(3.35)	(-0.96)	(3.33)
Top1	-0.000*	0.001***	-0.000*
	(-1.74)	(2.80)	(-1.68)
Duality	0.000	-0.006	0.000
	(0.56)	(-1.26)	(0.54)
Indep	-0.000	-0.000	-0.000
	(-0.01)	(-1.16)	(-0.04)
Constant	0.024***	1.246***	0.026***
	(2.66)	(15.32)	(2.92)
Year	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
Sobel Test		Z = -2.327, P = 0.022	
N	20,621	20,621	20,621
R^2	0.179	0.063	0.179
Adj. R^2	0.178	0.062	0.178

Notes: We report t-statistics in parentheses below fully standardized coefficients. Standard errors are clustered at the firm level. Firm fixed effect and year fixed effect are both controlled. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We also report result of the Sobel Test, which is significant at 5% level.

Table 11. Information asymmetry mechanism

	(1) DebtCost	(2) FDISP	(3) DebtCost
Did	-0.001***	-0.291***	-0.001***
	(-2.75)	(-2.58)	(-2.69)
FDISP			0.000***
			(2.92)
State	0.001	0.484*	0.001
	(1.09)	(1.76)	(1.05)
Big_N	0.001***	-0.030	0.001***
	(2.81)	(-0.34)	(2.81)
Size	-0.001	0.150*	-0.001*
	(-1.62)	(1.71)	(-1.65)
Lev	0.002	-0.513	0.002
	(0.91)	(-1.41)	(0.94)
ROA	-0.022***	-9.575***	-0.021***
	(-6.65)	(-8.84)	(-6.36)
Growth	-0.002***	-0.737***	-0.001***
	(-6.30)	(-12.05)	(-5.99)
PPE	0.010***	0.637*	0.010***
	(5.53)	(1.85)	(5.50)
Interest	-0.000***	-0.002***	-0.000***
	(-18.06)	(-5.15)	(-17.99)
FCF	0.025***	-2.120***	0.025***
	(13.22)	(-4.09)	(13.29)
Loss	0.001	-2.309***	0.001**
	(1.63)	(-10.85)	(2.05)
Top1	-0.000**	-0.013**	-0.000**
	(-2.45)	(-2.56)	(-2.40)
Duality	0.000	-0.017	0.000
	(0.95)	(-0.17)	(0.95)
Indep	-0.000	0.003	-0.000
	(-0.59)	(0.40)	(-0.60)
Constant	0.035***	-1.497	0.035***
	(3.80)	(-0.80)	(3.82)
Year	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
SobelTest		Z = -2.214, P = 0.019	
N	17,935	17,935	17,935
R^2	0.176	0.055	0.177
Adj. R^2	0.175	0.054	0.176

Notes: We report t-statistics in parentheses below fully standardized coefficients. Standard errors are clustered at the firm level. Firm fixed effect and year fixed effect are both controlled. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We also report result of the Sobel Test, which is significant at 5% level.

Table 12. Enterprise agency cost differences

	(1) DebtCost
*Did*HAC*	-0.001**
	(-1.98)
Did	-0.001*
	(-1.72)
HAC	0.001***
	(2.64)
State	0.001
	(1.15)
Big_N	0.001**
	(2.56)
Size	-0.000
	(-0.95)
Lev	0.002
	(1.44)
ROA	-0.019***
	(-6.66)
Growth	-0.001***
	(-5.41)
PPE	0.006***
	(3.36)
Interest	-0.000***
	(-19.82)
FCF	0.022***
	(12.57)
Loss	0.001***
	(2.58)
Top1	-0.000*
	(-1.88)
Duality	0.000
	(0.36)
Indep	0.000
	(0.45)
Constant	0.028***
	(3.29)
Year	Yes
Firm	Yes
Cluster	Yes
N	22,733
R^2	0.151
Adj. R^2	0.150

Notes: We report t-statistics in parentheses below fully standardized coefficients. Standard errors are clustered at the firm level. Firm fixed effect and year fixed effect are both controlled. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 13. Regional differences

	(1) DebtCost
*Did*Region*	-0.002**
	(-2.28)
Did	0.000
	(0.22)
State	0.001
	(1.19)
Big_N	0.001**
	(2.51)
Size	-0.000
	(-1.20)
Lev	0.002
	(1.52)
ROA	-0.019***
	(-6.54)
Growth	-0.001***
	(-5.20)
PPE	0.006***
	(3.44)
Interest	-0.000***
	(-19.91)
FCF	0.023***
	(12.85)
Loss	0.001**
	(2.55)
Top1	-0.000*
	(-1.92)
Duality	0.000
	(0.36)
Indep	0.000
	(0.43)
Constant	0.030***
	(3.62)
Year	Yes
Firm	Yes
Cluster	Yes
N	22,733
R^2	0.151
Adj. R^2	0.150

Notes: We report t-statistics in parentheses below fully standardized coefficients. Standard errors are clustered at the firm level. Firm fixed effect and year fixed effect are both controlled. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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