Low-Carbon City Pilot Policy and Green Investors Entry

Yong Jiang

Xiao Ding

Yi-Shuai Ren

Xiaolin Kong

Konstantinos Baltas

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Yong Jiang
School of Finance, Nanjing Audit University, Nanjing, China
Email: jiangziya.ok@163.com

Xiao Ding
School of Finance, Nanjing Audit University, Nanjing, China
Email: MP2205109@stu.nau.edu.cn

Yi-Shuai Ren*
School of Public Administration, Hunan University, China
Research Institute of Digital Society and Blockchain, Hunan University, China
Center for Resource and Environmental Management, Hunan University, China
The Energy Centre, University of Auckland, 12 Grafton Rd, Auckland, 1010, New Zealand
Email: renyishuai1989@126.com

Xiaolin Kong
Business School, Hunan University, China
Research Institute of Digital Society and Blockchain, Hunan University, China
Email: kongxiaolin@hnu.edu.cn

Konstantinos Baltas
Essex Business School, University of Essex, United Kingdom
Email: k.baltas@essex.ac.uk

Declaration of competing interest

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Data availability

Data will be made available on request.

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* Corresponding author.
E-mail: renyishuai1989@126.com (Yi-Shuai Ren).

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Abstract

Using low-carbon city pilot policy as a natural experiment, this study investigates whether low-carbon city pilot policy can help enterprises attract green investor entry in China. The results show that low-carbon city pilot policy significantly attracts green investor entry, which is more pronounced in non-state-owned enterprises and heavily polluting enterprises. Mechanism studies indicate that low-carbon city pilot policy facilitates green investor entry by alleviating financing constraints and strengthening enterprises' risk-taking.

Keywords: Low-carbon city pilot policy; Green investor entry; Difference-in-differences model

1. Introduction

As governments attach greater importance to environmental protection, carbon emission reduction and sustainable development (Ren et al., 2024b; Boubaker et al., 2024), a special category of institutional investors has formed, called green investors. Compared with neutral investors, green investors refuse to hold stocks of enterprises with environmentally polluting technologies (Barneae et al., 2005). Green investment accelerates industrial upgrading and drives technological progress, which helps control environmental pollution from the source (Ren et al., 2022). Nevertheless, the

substantial initial investment requirements, prolonged return on investment timelines, and the inherent market and technological uncertainties linked to green investment initiatives often dissuade numerous green investors. Amidst China's pursuit of green transition and stable economic expansion, the strategy to attract green investors has been integrated into the nation's medium to long-term development agenda (Zhang and Yusuf, 2020).

It has been widely confirmed that a country's economic policy significantly impacts business operations and investment activities (Ren et al., 2024a). This study primarily attempts to explore whether China's Low-Carbon City Pilot Policy (LCCP) started in 2010 has influenced the decision-making of green investors. With the expansion of pilot cities, many studies on the impacts of the LCCP, including urban ecological performance (Song et al., 2020), carbon emission reduction efficiency (Zeng et al., 2023), and enterprise-related indicators (Liu et al., 2023; Chen et al., 2024), have increased (Liu and Lv, 2023). However, the question of how the LCCP attracts green investor entry (GIE) remains unanswered.

To this end, this study employs LCCP as a quasi-natural experiment and employs the difference-in-differences (DID) model to examine the impact of LCCP on Chinese enterprises' attraction to GIE.

The main contributions of this study are as follows. On the one hand, to the best of the authors' knowledge, this is the first study to explore the role of LCCP in attracting GIE, further enriching relevant studies on the evaluation of the effect of LCCP. On the other hand, this study explores the potential mechanism by which LCCP policies

significantly attract GIE, which also provides new and essential insights into solutions for introducing GIE by improving LCCP.

2. Hypothesis development

The Chinese government has established the LCCP to address and mitigate climate change issues better (Ren et al., 2024c). LCCP began in 2010, and its implementation scope was gradually expanded in 2012 and 2017 (see Appendix B for details). We speculate that LCCP mainly helps companies attract green investors entry through financing constraint mitigation mechanisms and risk-taking enhancement mechanisms.

Financing constraint mitigation mechanisms. LCCP is closely related to economic incentives such as government direct investment, subsidies, and preferential credit policies (Zhao et al., 2019). These measures can directly alleviate the financial burden on enterprises, enhance corporate reputation, and improve their financing capabilities. Furthermore, the policy encourages enterprises to adopt efficient, energy-saving production methods and innovative technologies (Pan et al., 2022). According to the "Signaling Theory" (Baumo and Oates, 1988), this not only helps reduce the operational costs for enterprises but also enhances the competitiveness of products and services, boosts investor confidence, and increases support from financial institutions. Therefore, LCCP can enhance its attractiveness to GIE by reducing financing constraints for pilot enterprises.

Risk-taking enhancement mechanisms. LCCP is often accompanied by governmental support, which is beneficial in reducing the initial investment risks for enterprises. LCCP aids in enhancing an enterprise's market image and brand value,

bolstering consumer and investor trust, thereby, to some extent, mitigating market risks and augmenting the enterprise's risk-bearing capacity. A substantial body of research indicates that investors tend to invest in enterprises with a stronger capacity to withstand risks. Based on the preceding discussion, we propose the following hypothesis.

Hypothesis 1: The low-carbon city pilot policy can help enterprises attract green investor entry.

3. Empirical design

3.1 Baseline model

To estimate the relation of the LCCP on the GIE, we develop the following regression model:

$$GIE_{i,t} = \beta_0 + \beta_1 DID_{c,t} + \beta_2 Control + \eta_{ind} + \eta_{year} + \varepsilon_{i,t} \quad (1)$$

Where the subscripts *c*, *i* and *t* represent city, enterprises and years, respectively. $DID_{i,t}$ is the core explanatory variable. If city *c* is included in the LCCP in and after year *t*, $DID_{i,t} = 1$; otherwise, $DID_{i,t} = 0$, *Controls* denotes the control variables. We also control the industrial fixed effect (η_{firm}) and the time-fixed effect (η_{year}). $\varepsilon_{i,t}$ is the independent and identically distributed residuals. Robust standard errors are clustered at the enterprise level for all estimates.

3.2 Data and variables

We select China's A-share listed enterprises as the research sample. Meanwhile, to ensure the unity and stability of policy effects, panel data from 2008 to 2020 was constructed. The enterprise-level data required for calculations come from the Wind and CSMAR databases. See Tables A1 and A2 of Appendix A for variable information

and descriptive statistics, respectively.

4. Main results

4.1 Baseline model

We regard LCCP as a quasi-natural experiment and use the progressive DID method to examine the impact of LCCP on Chinese enterprises' attraction to GIE. The regression results are shown in Table 1. In detail, Column (1) reports the results without adding control variables, which show that the coefficient of *DID* is significantly positive at the 1% level, indicating that LCCP can increase GIE. After controlling the corporate financial variables, the regression results in Column (2) show that the coefficient of *DID* has changed slightly but is still significantly positive. Column (3) simultaneously controls characteristic variables at the corporate financial and governance levels, which shows that the coefficient of *DID* is significantly positive at the 1% level. The above results confirm that our hypothesis is supported.

Insert Table 1 here

4.2 Robustness test

4.2.1 The test of parallel trend assumption

To test whether the DID model satisfies the parallel trend assumption[1], we construct the following model (2) for testing:

$$GIE_{i,t} = \beta_0 + \beta_1 \sum_{t=-2}^{t=6} Treat_c \times Year_t + \beta_2 Control + \eta_{ind} + \eta_{year} + \varepsilon_{i,t} \quad (2)$$

where $Year_t$ denotes a dummy variable for relative years. Specifically, if a given year

[1] The DID model needs to satisfy the parallel trend assumption, that is, there is no significant difference between the experimental group and the control group over time before the policy occurs.

aligns with the establishment year of LCCP, $Year_t$ is marked as *Current*. If it is 1 (or 2) year (s) before the start of the LCCP, $Year_t$ is noted as *before*1 (*before*2). Similarly, if it's 1 (or 2) year (s) after the pilot's initiation, $Year_t$ is denoted as *post*1 (*post*2), and so on. This study investigates the trend changes two years before and six years after the pilot policy's implementation. We use the first period before the policy is introduced as the base year.

Figure 1 lists the parallel trend test plots. We find that the coefficient of *DID* is not significantly different from zero before LCCP since its 95% confidence interval contains a value of zero. Conversely, after policy implementation, the DID regression coefficient significantly exceeds zero, confirming the DID model meets the parallel trend assumption.

Insert Figure 1 here

4.2.2 PSM-DID model

We use the propensity score matching model (PSM) to alleviate the endogeneity problem caused by sample selection bias and perform a robustness test. After we use the new sample data based on the nearest neighbour matching method 1:1, the nearest neighbour matching method 1:2, the radius matching method and the kernel matching method, the coefficients of *DID* are shown in Table 2, respectively. We find the coefficients of *DID* all pass the significance test at the 1% level, confirming that LCCP promotes GIE significantly.

Insert Table 2 here

4.2.3 Placebo test

We conduct a placebo test by randomly selecting samples from the experimental group. We repeat the above process 500 times, and the specific results are shown in Figure 2. It can be seen that most of the estimated coefficients are concentrated near zero, which is far lower than the coefficients obtained by the baseline regression in this study, and the p values are mostly greater than 0.1 (that is, not significant at the 10% level). This shows that the baseline regression results of this study are not obtained by chance, which further supports the robustness of the benchmark regression results.

Insert Figure 2 here

4.2.4 Policy exogeneity test

To exclude the influence of expectancy effect, we exclude the data from the year before the policy was implemented (the year 2009) to reduce the potential endogeneity problems caused by the expected effects on enterprises. The regression results in Column (2) of Table 3 shows that the regression coefficient of the *DID* has not changed fundamentally, indicating that no expectancy effect affects the exogeneity condition of policy shocks.

4.2.5 Alternative dependent variable

To demonstrate the robustness of our conclusions, we alternative the dependent variables by constructing a dummy variable, *GI_dummy*, which takes a value of 1 if the enterprise has a green investor entering; otherwise, it takes a value of 0. We add *GI_dummy* into the Eq. (1) to regress. The regression results are shown in Column (4) of Table 3. We find that the coefficient of *DID* on the *GI_dummy* is significantly positive at the 1% level.

4.2.6 Alternative the sample interval

China's stock market plummeted in 2015 and the COVID-19 outbreak broke out in 2020. These may affect the behavior of green investors and cause biased regression results. Therefore, we eliminated the data in 2015 and 2020 and re-estimated Eq. (1). The results are shown in Column (1) in Table 3. In addition, to avoid possible sample selection bias, we eliminate the samples from four municipalities (Beijing, Shanghai, Tianjin, and Chongqing) and re-estimate the Eq. (1). The results are shown in Table 3, which confirm that LCCP still has a significant positive effect on GIE.

4.2.7 Alternative the estimation model

The OLS estimate may be biased since the explained variable GIE has a non-negative integer-skewed distribution. Therefore, we use the Tobit model and the Poisson distribution model for estimation. Column (5) of Table 3 shows the regression results using the mixed Tobit model. Column (6) of Table 3 displays the regression results using the Poisson distribution model. The results from the two models show that the *DID* is significantly positive at the 1% level, further verifying the robustness of our results.

Insert Table 3 here

4.3 Mechanism analysis

This section mainly discusses the channels through which LCCP affects the GIE from corporate financing constraints and corporate risk-taking.

4.3.1 Risk-taking Enhancement Mechanism

Referring to John et al. (2008), we measure the level of corporate risk-taking by

the volatility of return on assets (*ROA*), Labeled *Risk*, which is used in many papers (Li et al., 2013; He et al., 2023). The larger the *Risk*, the higher the risk-taking level for a firm. We directly verify whether LCCP further affects GIE by risk-taking. The estimation results in Columns (1) and (2) of Table 4 show that LCCP significantly increases the risk-taking level of listed enterprises, and the increase in risk-taking significantly attracts GIE. This indicates that enhancing the level of risk-taking by enterprises is a key mechanism through which the LCCP promotes the GIE.

4.3.2 Financing Constraint Mitigation Mechanism

We choose the Whited-Wu (*WW*) index of financial constraints (Whited & Wu, 2006) as a proxy variable for corporate financing constraints. Columns (3) and (4) of Table 4 show that the LCCP significantly reduces the financing constraints of listed enterprises, and the weakening of financing constraints helps attract GIE. This demonstrates that alleviating financing constraints is a crucial mechanism through which the LCCP facilitates the GIE.

Insert Table 4 here

4.4 Cross-section tests

4.4.1 SOEs VS non-SOEs

To examine the differences in the impact of LCCP on attracting GIE to enterprises with different ownership structures, we divide the sample into state-owned enterprises (*SOE*=1) and non-state-owned enterprises (*SOE*=0) and re-estimate Eq. (1), respectively. The results are shown in Columns (1) and (2) of Table 5. We find that LCCP does not significantly attract GIE among state-owned enterprises (SOEs) but is

valid in non-SOEs. This once again proves the establishment of financing constraint channels.

4.4.2 Heavy polluting industries versus non-heavy polluting industries

This mainly explores whether there is a significant difference in the impact of LCCP on GIE between polluting (*Heavy*=1) and non-polluting industries (*Heavy*=0). Following Chen et al. (2024), Columns (3) and (4) of Table 5 compare the impact of LCCP on heavily polluting industries and non-heavy polluting industries. We find LCCP significantly increases GIE in heavily polluting firms, but the effect of LCCP is not significant in non-heavy polluting firms.

Insert Table 5 here

5. Conclusion

This study takes China's A-share listed enterprises from 2008 to 2020 as the sample and uses China's LCCP as a quasi-natural experiment to empirically test the impact of LCCP on the GIE. We find that LCCP has significantly promoted GIE. Easing corporate financing constraints and improving corporate risk-taking levels are important mechanisms through which LCCP affects GIE. The heterogeneity test finds that the attraction effect of LCCP is more prominent among non-SOEs and enterprises in the high-pollution industry. Our study suggests that the government can further introduce proactive green policies in the future to aid businesses in enhancing their capacity to attract investor entry. Additionally, this study still has room for expansion, such as further exploring the economic consequences of green investor entry.

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Appendix

Appendix A

Insert Table A1 here

Insert Table A2 here

Appendix B: Institutional background

LCCP is an important measure for China to respond to the challenge of global climate change and promote domestic sustainable development. Since its launch in 2010, the policy has gone through multiple stages of evolution, gradually expanding the scope of pilot cities and continuously deepening the practice of low-carbon development.

In 2010, the Chinese National Development and Reform Commission (NDRC) launched the pilot work of low-carbon provinces and low-carbon cities for the first time, selecting 5 provinces and 8 cities as the first batch of pilot projects, aiming to explore a low-carbon development path that adapts to Chinese conditions. These pilot areas are required to formulate low-carbon development plans, implement carbon emission control actions, and establish carbon emission statistics and monitoring systems. By 2012, the second batch of low-carbon city pilot lists was announced, adding 3 provinces and 28 cities. The pilots at this stage pay more attention to the integration of low-carbon city construction and local economic and social development, emphasizing innovation in industrial structure adjustment, energy structure optimization, building energy conservation and traffic management. In 2017, China once again expanded the scope of low-carbon city pilots and added many new cities, which shows that the Chinese

government regards low-carbon development as an important direction for transformation and upgrading. Pilot cities have achieved certain results in promoting the application of green and low-carbon technologies, developing a circular economy, and building green buildings and transportation systems.

As the international community pays more attention to climate change, the Chinese government committed in its Nationally Determined Contribution (NDC) to the Paris Agreement submitted in 2015 to reduce carbon dioxide emissions per unit of gross domestic product (GDP) by 60% by 2030 compared with 2005 levels. LCCP plays an important role in this context and has become an important starting point for realizing the country's emission reduction commitments.

So far, LCCP in China has continued to deepen, the number of pilot cities has continued to increase, and the concept of low-carbon development has been deeply rooted in the hearts of the people. These pilot cities have accumulated valuable experience in promoting energy-saving and emission-reduction technologies, developing a green economy, and raising public awareness of environmental protection, providing examples and models for low-carbon development across the country and around the world. In the future, LCCP is expected to continue to promote the transition from policy guidance to market-driven development to achieve broader and deeper low-carbon development. Our research not only supplements the existing literature on LCCP effect evaluation, but also contributes to corporate green innovation and sustainable development.

Figures

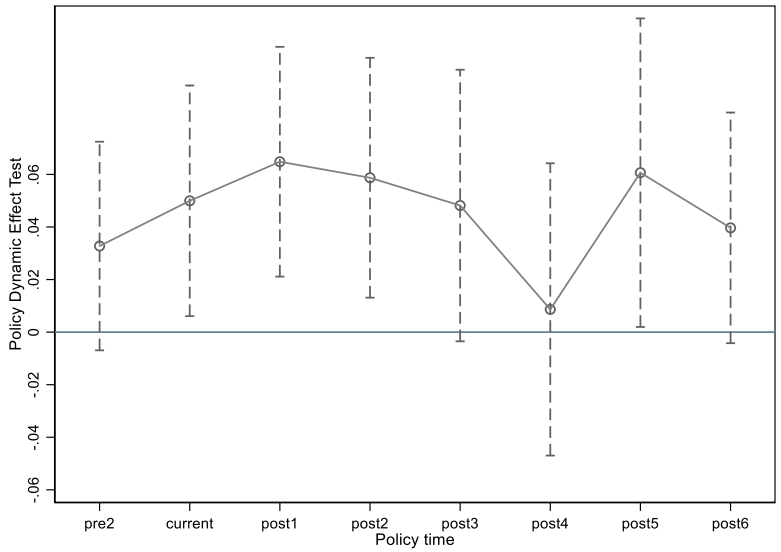

Figure 1 Parallel trend test plot

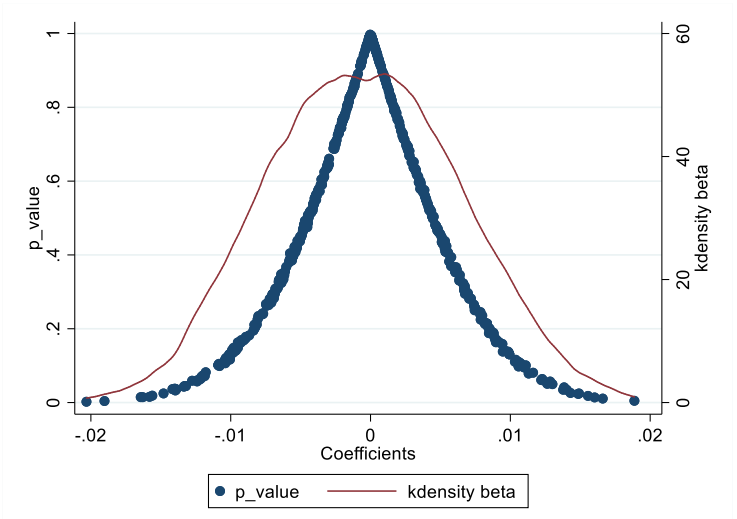

Figure 2 Placebo test diagram

Tables

Table 1 Baseline results

Variables	(1) *GIE*	(2) *GIE*	(3) *GIE*
DID	0.0554***	0.0267*	0.0293**
	(2.67)	(1.84)	(2.04)
Size		0.3272***	0.3367***
		(41.12)	(41.32)
Lev		-0.1349***	-0.1357***
		(-3.68)	(-3.69)
ROA		3.1908***	3.2652***
		(32.28)	(32.51)
Cashflow		0.0170	0.0497
		(0.24)	(0.70)
Cap		1.0100***	0.9702***
		(8.79)	(8.49)
TobinQ		0.1821***	0.1811***
		(29.85)	(29.62)
FirmAge		-0.1645***	-0.1742***
		(-7.77)	(-8.31)
Board			-0.0039
			(-0.10)
Indep			-0.1110
			(-0.84)
Dual			0.0703***
			(5.38)
Top1			-0.3604***
			(-7.96)
Year FE	YES	YES	YES
Ind FE	YES	YES	YES
Adj.R^2	0.0785	0.359	0.364

Notes: Reported in parentheses are T-statistics based on robust standard errors clustered at the enterprise level. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. FE, fixed effects.

Table 2 PSM-DID model results

Variables	(1) *GIE* Nearest neighbor matching method 1:1	(2) *GIE* Nearest neighbor matching method 1:2	(3) *GIE* Radius matching method	(4) *GIE* Kernel matching method
DID	0.0366**	0.0326*	0.0294**	0.0294**
	(1.98)	(1.94)	(2.04)	(2.04)
Size	0.3435***	0.3394***	0.3367***	0.3367***
	(31.10)	(36.44)	(41.14)	(41.14)
Lev	-0.1707***	-0.1433***	-0.1351***	-0.1351***
	(-3.46)	(-3.39)	(-3.67)	(-3.67)
ROA	3.1720***	3.2341***	3.2666***	3.2666***
	(22.44)	(26.25)	(32.50)	(32.50)
Cashflow	0.0610	-0.0376	0.0487	0.0487
	(0.60)	(-0.43)	(0.68)	(0.68)
Cap	0.9502***	1.0112***	0.9720***	0.9720***
	(6.17)	(7.50)	(8.50)	(8.50)
TobinQ	0.1977***	0.1883***	0.1811***	0.1811***
	(22.99)	(25.93)	(29.48)	(29.48)
FirmAge	-0.1561***	-0.1561***	-0.1741***	-0.1741***
	(-5.53)	(-6.35)	(-8.30)	(-8.30)
Board	-0.0249	-0.0148	-0.0029	-0.0029
	(-0.48)	(-0.33)	(-0.08)	(-0.08)
Indep	-0.3314*	-0.2285	-0.1042	-0.1042
	(-1.79)	(-1.41)	(-0.79)	(-0.79)
Dual	0.0712***	0.0685***	0.0708***	0.0708***
	(3.91)	(4.40)	(5.42)	(5.42)
Top1	-0.3790***	-0.3482***	-0.3606***	-0.3606***
	(-6.42)	(-6.68)	(-7.96)	(-7.96)
Year FE	YES	YES	YES	YES
Ind FE	YES	YES	YES	YES
Adj.R^2	0.374	0.365	0.363	0.363

Notes: Reported in parentheses are T-statistics based on robust standard errors clustered at the enterprise level. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. FE, fixed effects.

Table 3 Robustness Test

Variables	(1) *GIE* Remove year of 2020	（2） *GIE* Remove year of 2009	(3) *GIE* Remove municipalities	(4) *GIEDUM* Change GIE	(5) *GIE* Tobit model	(6) *GIE* Poisson model
DID	0.0265*	0.0289**	0.0350**	0.0222**	0.0596***	0.1963***
	(1.78)	(2.00)	(2.26)	(2.47)	(0.0193)	(0.0241)
Size	0.3375***	0.3386***	0.3446***	0.1776***	0.6288***	0.4607***
	(39.34)	(41.13)	(36.56)	(44.91)	(0.0092)	(0.0121)
Lev	-0.0849**	-0.1461***	-0.1398***	-0.1081***	-0.3117***	-0.3250***
	(-2.22)	(-3.87)	(-3.47)	(-4.53)	(0.0561)	(0.0766)
ROA	3.3837***	3.3129***	3.2725***	1.8941***	7.4464***	6.2570***
	(30.86)	(32.27)	(29.56)	(29.79)	(0.1845)	(0.2163)
Cashflow	0.1489**	0.0354	0.0574	0.0267	-0.2416*	-0.8062***
	(1.97)	(0.48)	(0.71)	(0.57)	(0.1357)	(0.1426)
Cap	0.8401***	1.0056***	0.8880***	0.6394***	2.3470***	1.7496***
	(7.15)	(8.51)	(7.15)	(8.80)	(0.1791)	(0.2012)
TobinQ	0.1817***	0.1817***	0.1799***	0.0739***	0.2647***	0.1940***
	(24.67)	(29.02)	(26.27)	(20.93)	(0.0079)	(0.0096)
FirmAge	-0.1364***	-0.1789***	-0.1400***	-0.1099***	-0.3707***	-0.2879***
	(-6.50)	(-8.33)	(-5.97)	(-8.56)	(0.0258)	(0.0318)
Board	-0.0003	0.0015	-0.0233	0.0220	0.0429	-0.0829
	(-0.01)	(0.04)	(-0.55)	(0.95)	(0.0505)	(0.0663)
Indep	-0.1369	-0.0872	-0.1395	-0.1608**	-0.4870***	-0.5227**
	(-0.99)	(-0.65)	(-0.96)	(-2.00)	(0.1785)	(0.2471)
Dual	0.0615***	0.0710***	0.0723***	0.0398***	0.1375***	0.1418***
	(4.48)	(5.34)	(4.94)	(4.88)	(0.0186)	(0.0233)
Top1	-0.3349***	-0.3647***	-0.3916***	-0.1808***	-0.6936***	-0.8743***
	(-7.11)	(-7.90)	(-7.68)	(-6.61)	(0.0571)	(0.0828)
Year FE	YES	YES	YES	YES	YES	YES
Ind FE	YES	YES	YES	YES	YES	YES
Adj.R^2(Pseudo R^2)	0.375	0.365	0.365	0.266	0.1751	0.1456

Notes: Reported in parentheses are T-statistics based on robust standard errors clustered at the enterprise level. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. FE, fixed effects.

Table 4 Plausible mechanisms analysis

Variables	(1) *Risk*	(2) *GIE*	(3) *WW*	(4) *GIE*
DID	0.0012*		-0.0020***	
	(1.72)		(-2.96)	
Risk		0.2900**		
		(2.01)		
WW				-0.9495***
				(-6.62)
Size	-0.0035***	0.3387***	-0.0477***	0.3020***
	(-10.75)	(41.53)	(-129.91)	(28.46)
Lev	-0.0150***	-0.1321***	0.0103***	-0.1228***
	(-6.58)	(-3.58)	(4.78)	(-3.12)
ROA	-0.1278***	3.3152***	-0.2796***	2.8296***
	(-15.56)	(31.75)	(-49.43)	(24.36)
Cashflow	0.0151***	0.0499	-0.0830***	0.0432
	(3.40)	(0.70)	(-19.39)	(0.56)
Cap	-0.0211***	0.9806***	-0.0191***	0.9647***
	(-3.74)	(8.56)	(-3.63)	(8.12)
TobinQ	0.0021***	0.1806***	0.0027***	0.1999***
	(6.23)	(29.53)	(9.40)	(29.36)
FirmAge	-0.0036***	-0.1739***	0.0050***	-0.1481***
	(-3.74)	(-8.27)	(5.62)	(-6.81)
Board	-0.0045**	-0.0031	0.0002	-0.0169
	(-2.44)	(-0.08)	(0.13)	(-0.41)
Indep	0.0029	-0.1074	0.0064	-0.0840
	(0.46)	(-0.82)	(1.09)	(-0.60)
Dual	0.0029***	0.0705***	-0.0016***	0.0667***
	(4.28)	(5.39)	(-2.64)	(4.74)
Top1	-0.0060***	-0.3567***	-0.0068***	-0.3966***
	(-2.88)	(-7.89)	(-3.31)	(-8.33)
Year FE	YES	YES	YES	YES
Ind FE	YES	YES	YES	YES
Adj.R^2	0.143	0.365	0.818	0.383

Notes: Reported in parentheses are T-statistics based on robust standard errors clustered at the enterprise level. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. FE, fixed effects.

Table 5 Cross-section test

Variables	(1) *GIE* *SOE*=1	(2) *GIE* *SOE*=0	(3) *GIE* *Heavy*=1	(4) *GIE* *Heavy*=0
DID	0.0113	0.0384**	0.0606**	0.0124
	(0.51)	(2.11)	(2.45)	(0.70)
Size	0.3413***	0.3458***	0.3127***	0.3467***
	(27.77)	(30.56)	(21.53)	(35.50)
Lev	-0.1266**	-0.1251***	-0.1492**	-0.1372***
	(-2.11)	(-2.65)	(-2.26)	(-3.13)
ROA	3.1539***	3.2517***	2.9429***	3.3638***
	(16.87)	(27.47)	(14.89)	(28.94)
Cashflow	0.3414***	-0.1368	0.0407	0.0767
	(3.12)	(-1.47)	(0.29)	(0.93)
Cap	0.5139***	1.1565***	1.2502***	0.8360***
	(2.79)	(8.07)	(6.44)	(5.91)
TobinQ	0.2103***	0.1684***	0.1815***	0.1809***
	(19.89)	(22.40)	(14.69)	(25.93)
FirmAge	-0.1343***	-0.1577***	-0.1717***	-0.1732***
	(-3.56)	(-6.31)	(-3.98)	(-7.28)
Board	0.0760	-0.0118	0.0912	-0.0464
	(1.35)	(-0.23)	(1.35)	(-1.00)
Indep	-0.0881	-0.0814	0.1022	-0.2210
	(-0.44)	(-0.47)	(0.45)	(-1.39)
Dual	0.0487*	0.0551***	0.0835***	0.0661***
	(1.76)	(3.71)	(3.54)	(4.30)
Top1	-0.3193***	-0.3056***	-0.3331***	-0.3669***
	(-4.61)	(-5.18)	(-3.77)	(-7.03)
Year FE	YES	YES	YES	YES
Ind FE	YES	YES	YES	YES
Adj.R^2	0.436	0.336	0.345	0.372

Notes: Reported in parentheses are T-statistics based on robust standard errors clustered at the enterprise level. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. FE, fixed effects.

Table A1 Variable definitions and constructions

	Variable	Definition
Dependent variable	*GIE*	Natural logarithm of the number of green investors plus 1 at the end of year
Independent variable	*DID*	Dummy variable, if city is included in the LCCP in and after the pilot year, it is 1, otherwise 0
Control variable	*Size*	Natural logarithm of the firm's total assets at the end of the year
	Lev	Total liabilities at the end of year / Total assets at the end of year
	ROA	Net profit / average balance of total assets
	Cashflow	Net cash flow from operating activities/total assets at the end of the year
	TobinQ	Market value of equity scaled by total assets
	FirmAge	ln (current year - year of incorporation +1)
	Board	Natural logarithm of the total number of board members
	Indep	Percentage of independent directors on the board
	Dual	Dummy variable, 1 for the same person as the chairman and managing director; 0 if not the same person
	Top1	Shareholding of the largest shareholder at the end of the year as a proportion of the total shares of the firm

Notes: The sample is screened according to the following procedures. Firstly, observations of firms in the financial sector were excluded. Secondly, the observations of S.T. firms and *S.T. firms during the sample period were excluded. Thirdly, observations lacking relevant financial data were excluded. All continuous variables are winsorized at the 1% and 99% levels to avoid biasing the results due to extreme values. The final sample covers 3512 A-shared listed companies, with 28409 firm-year observations.

Table A2 Descriptive statistics

VarName	Obs	Mean	Max	Min	Median	SD
GIE	28409	0.5709	2.9444	0.0000	0.0000	0.7682
LCCP	28409	0.5661	1.0000	0.0000	1.0000	0.4956
Size	28409	22.1222	25.9337	19.9195	21.9261	1.2876
Lev	28409	0.4200	0.8715	0.0555	0.4133	0.2070
ROA	28409	0.0465	0.2085	-0.1698	0.0424	0.0582
Cashflow	28409	0.0486	0.2316	-0.1490	0.0479	0.0687
Cap	28409	0.0511	0.2315	0.0003	0.0368	0.0480
TobinQ	28409	1.9862	7.5606	0.8810	1.5970	1.1931
FirmAge	28409	2.8088	3.4657	1.6094	2.8904	0.3727
Board	28409	2.1380	2.7081	1.6094	2.1972	0.1988
Indep	28409	0.3741	0.5714	0.3333	0.3333	0.0528
Dual	28044	0.2673	1.0000	0.0000	0.0000	0.4425
Top1	28409	0.3517	0.7306	0.0900	0.3334	0.1496