The effects of state capital injection on firms' green innovation

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Online Appendix

Appendix A. Appendix to section 3

A1. Definition and measurement methods of mechanism variables

Green innovation capability. We measure firms, green innovation capability from three dimensions: (1) Resource acquisition capability (*KZ_index*). We employ the KZ index developed by Kaplan and Zingales (1997) to quantify firms' resource acquisition capability. A higher *KZ_index* signifies more severe financing constraints faced by the firm. (2) Human capital level (*Bachelor_r*). We use the proportion of employees with bachelor's degrees to measure a firm's attractiveness to high-quality talent. Existing research posits that a larger number of employees with higher education reflects a higher human capital level (Sun *et al.,* 2020). (3) Joint R&D opportunities (*R&D_co*). We use the ratio of green invention patents jointly applied for by the firm in a given year to its total green patent applications to measure the likelihood of joint R&D. Joint R&D not only facilitates access to new technical resources but also enhances a firm's innovative potential, aiding it in better completing R&D projects (Prabhu, 1997).

Green innovation willingness (*R&D_exp*). We measure firms' innovation willingness by the logarithm of their R&D expenditure. R&D expenditure represents firms' innovation investment and can effectively reflect their willingness to innovate.

Environmental Regulatory Pressure (*Fee_po*). Following Huang *et al.* (2020), we use the proportion of sewage charges (taxes) that firms need to pay as a percentage of their sales revenue to measure the environmental regulatory pressures faced by firms.

Managerial myopia (*Myopia*). Following established research protocols, managerial myopia among firms is operationalized as the ratio of management-myopia-related word counts in management discussion and analysis texts to total vocabulary (Lu *et al.,* 2024). Word frequency data for managerial myopia are sourced from the CNRDS database.

Agency problems. Given the presence of two types of agency problems in firms: those between shareholders and management, and between controlling and minority shareholders. we measure both categories of agency conflicts. (1) Type I principal-agent problems, following Ang *et al.* (2000) and Jiang *et al.* (2010), we utilize the management cost ratio (*M_cost*) to measure the agency costs related to monitoring, guaranteeing, and excessive consumption by managers. Meanwhile, we have employed the total asset turnover ratio (*TR*) to measure the agency costs resulting from the inefficient use of assets by managers. (2) Type II principal-agent problems (*PP_Cost*). Given that other receivables represent a primary form of fund appropriation from large shareholders, following Jiang *et al.* (2010), we measure the principal-agent costs between large and small shareholders using the ratio of other accounts receivable.

Policy burden（*PB*）. We used the excess employee rate to quantify the policy burden faced by firms (Bai *et al.,* 2006). Specifically, *PB* = (Number of employees − Sales revenue × $\frac{\text{Industry Average Number of Employees}}{\text{Industry Average Sales Revenue}}$) / Number of employees.

A2. Control variables' definitions

Table A1. The definition of control variables

Variables	Definition
Age	The number of years since a firm has been listed on a stock exchange.
Sale	Measured by the natural log of main business revenue.
Leverage	Debt to assets ratio.
ROA	Return on assets.
Growth	The ratio of the current year's revenue from main business to the previous year's revenue from main business minus 1.
First	The proportion of shareholding of the largest shareholder.
Balance	The ratio of the number of shares held by the first largest shareholder to the number of shares held by the second to tenth largest shareholders.
Manage	The proportion of management shareholding.
Board	The total number of board members.
Supervisor	the number of people on the supervisory board.
Independ	The proportion of independent directors to the number of board members.
Duality	Takes a value of 1 if the CEO and the chairperson are the same person, 0 otherwise.

A3. Descriptive analysis

Table A2 provides the descriptive statistics for the variables, excluding the three interaction fixed effects. On average, firms that in treatment group exhibit a higher quantity and quality of green invention patent applications than firms that have not, in line with Hypothesis A. However, it is essential to note that this does not necessarily imply that SCI unconditionally enhances both the quantity and quality of firms' green innovation. This comparison merely reflects a cross-sectional disparity between the treatment and control groups, without capturing the actual effects of SCI in the treatment group (Jiang *et al.*, 2023).

Table A2. Descriptive statistics for variables

Variables	All samples		Control group		Treatment group		(7)
	(1) Mean	(2) S.D.	(3) Mean	(4) S.D.	(5) Mean	(6) S.D.	(5) – (3)
Inno_num	0.485	0.890	0.436	0.841	0.651	1.020	0.215 (0.016)
Inno_q1	0.101	0.196	0.095	0.193	0.121	0.205	0.026 (0.004)
SCID	0.085	0.278					
KZ_index	0.541	0.286	0.571	0.276	0.437	0.292	–0.135 (0.005)
Bachelor_r	24.52	17.33	24.45	17.56	24.74	16.56	0.282 (0.329)
R&D_co	0.034	0.130	0.0302	0.124	0.0477	0.148	0.018 (0.002)
R&D_exp	17.81	1.392	17.76	1.349	17.96	1.518	0.201 (0.027)
Fee_po	13.43	1.502	13.34	1.453	13.75	1.616	0.415 (0.030)
Myopia	3.243	0.453	3.254	0.458	3.206	0.434	–0.048 (0.008)
M_cost	10.83	7.349	11.16	7.533	9.744	6.582	–1.413 (0.131)
TR	2.180	1.597	2.207	1.638	2.097	1.456	–0.110 (0.030)
PP_Cost	1.130	2.354	1.122	2.378	1.158	2.273	0.035 (0.046)
PB	0.126	1.009	0.121	1.007	0.146	1.020	0.026 (0.029)
Age	7.933	7.029	7.274	6.836	10.01	7.222	2.741 (0.128)
Sale	21.31	1.363	21.20	1.336	21.64	1.394	0.436 (0.025)
Leverage	0.383	0.197	0.363	0.190	0.446	0.206	0.083 (0.004)
ROA	0.050	0.057	0.0526	0.059	0.042	0.048	–0.011 (0.001)
Growth	0.155	0.293	0.149	0.292	0.172	0.296	0.023 (0.005)
First	0.345	0.145	0.341	0.144	0.358	0.147	0.017 (0.003)
Balance	0.575	0.193	0.560	0.186	0.620	0.205	0.059 (0.004)
Manage	8.755	15.69	9.229	15.90	7.259	14.89	–1.969 (0.290)
Board	9.167	2.666	9.090	2.634	9.409	2.752	0.320 (0.049)
Supervisor	4.446	2.809	4.421	2.924	4.528	2.412	0.108 (0.052)
Independ	39.62	10.51	39.44	10.78	40.18	9.580	0.741 (0.195)
Duality	0.011	0.102	0.012	0.106	0.008	0.087	–0.004 (0.002)

Note: Standard errors are shown in parentheses.

Regarding mechanism variables, firms in the treatment group tend to exhibit higher resource acquisition capabilities, joint R&D opportunities, and innovation intent, face greater environmental regulatory pressure, and have less managerial myopia, lower administrative expense ratios, and lower total asset turnover rates. However, there are no significant differences between treatment and control group firms in human capital levels, Type II principal-agent problems, or policy burdens.

Regarding the control variables, firms that in treatment group tend to have a longer history of being listed on a stock exchange, higher main business revenue, a greater debt-to-asset ratio, a higher growth rate of their main business, a larger shareholding ratio of the largest first shareholder, a more balanced equity structure, a larger board of directors, a larger supervisory board, and a higher proportion of independent directors. Conversely, their ROA, management shareholding, and instances of CEO duality are lower.

Additionally, we calculated the correlation coefficients among core variables including *Inno_q1*, *Inno_num*, *SCID*, and mechanism variables, with the results presented in table A3. As shown, the correlation coefficient between *Inno_num* and *Inno_q1* exceeds 0.5, indicating a positive correlation between the quantity and quality of green innovation. *SCID* exhibits positive correlations with both *Inno_q1* and *Inno_num*, suggesting that SCI may enhance both the quantity and quality of firms' green innovation. Furthermore, all correlation coefficients between variables are below 0.6, implying no severe multicollinearity issues are likely to exist. Meanwhile, mechanism variables such as resource acquisition capability, human capital level, joint R&D opportunities, innovation intent, environmental regulatory pressure, managerial myopia, and policy burdens all show positive correlations with both the quantity and quality of firms' green innovation. By contrast, proxy variables for Type I and Type II principal-agent problems exhibit negative correlations with the quantity and quality of firms' green innovation.

Table A3. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) *Inno_q1*	1.000												
(2) *Inno_num*	0.598	1.000											
(3) *SCID*	0.092	0.154	1.000										
(4) *KZ_index*	–0.218	–0.371	–0.230	1.000									
(5) *Bachelor_r*	0.139	0.212	0.074	–0.086	1.000								
(6) *R&D_co*	0.289	0.353	0.080	–0.192	0.116	1.000							
(7) *R&D_exp*	0.268	0.427	0.134	–0.493	0.167	0.180	1.000						
(8) *Fee_po*	0.231	0.366	0.182	–0.488	0.021	0.200	0.548	1.000					
(9) *Myopia*	0.055	0.059	0.024	–0.098	0.049	0.050	0.110	0.094	1.000				
(10) *M_cost*	–0.013	–0.041	–0.049	0.279	0.313	–0.035	0.003	–0.464	0.037	1.000			
(11) *TR*	–0.016	–0.017	0.038	–0.014	0.197	–0.019	–0.212	–0.351	0.058	0.425	1.000		
(12) *PP_Cost*	–0.024	–0.043	0.036	0.003	0.028	–0.031	–0.100	–0.095	0.034	0.068	0.121	1.000	
(13) *PB*	0.053	0.100	0.019	–0.173	0.248	0.034	0.120	0.248	0.076	–0.273	–0.180	0.023	1.000

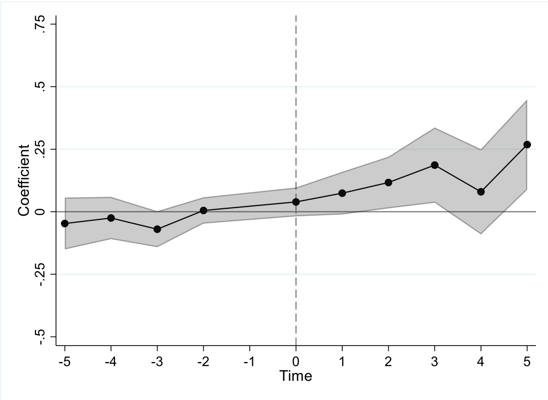
Appendix B. Robustness tests

B1. Parallel trends test

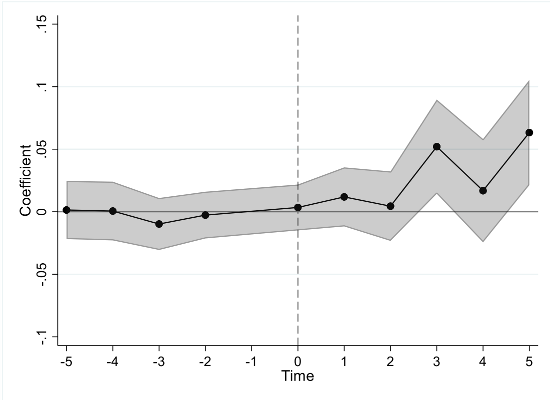
Estimation using the DID model relies on the assumption of parallel trends, which means that the treatment and control groups should demonstrate similar trends in the periods before and after treatment, assuming that the treatment did not occur. While it is not feasible to directly test this assumption in a counterfactual scenario where the treatment did not occur after the treatment time point, if the two groups satisfy the parallel trends assumption before the treatment, it reinforces our confidence in utilizing the DID model for estimation. Following Dong and Liu (2022) and Jiang *et al.* (2023), we employ the event study method to assess whether the two groups meet the pre-treatment parallel trends assumption, as outlined below:

$$Y_{it} = \alpha_0 + \beta_n \sum_2^5 Before_{in} \times Treat_i + \rho_m \sum_0^5 After_{im} \times Treat_i + X'\psi + \gamma_i + \delta_t + \epsilon_{it}, \tag{A1}$$

where $Before_n$ represents the n-th year before the implementation of SCI, and $After_m$ represents the m-th year after the implementation of SCI. If β_n is not statistically significant, this suggests that the pretreatment parallel trends assumption is met. Figures A1(a) and A1(b) display the results of the pretreatment parallel trends tests. It can be observed that both the quantity and quality of green innovation do not exhibit significant differences between the treatment and control groups before the implementation of SCI. Consequently, the pretreatment parallel trends assumption is valid.



(a) Quantity of patents



(b) Quality of patents

Figure A1. Results of parallel trends tests.
The horizontal coordinate represents the relative year before or after the year of implementation of SCI. Shaded areas represent 90% confidence intervals. Panels (a) and (b) show the result of parallel trends test using *Inno_num* and *Inno_q1* as the dependent variable, respectively. All control variables in the baseline model are included when conducting the estimation.

B2. Replacing the dependent variable

As the measurement of innovation indicators can potentially influence the estimation results, we conduct robustness checks by substituting the measures of green innovation. Specifically, for the quantity of green innovation, we employ the number of green utility patents filed in the year (*Utility_num*) as a proxy. We replace the quality of green innovation with the previously constructed median value of the knowledge width of patents for a firm (*Inno_q2*). Additionally, following Aghion *et al.* (2019), we utilize the annual average citation count within five years after the application date for green invention patents filed in the year (*Mcite*) as an alternative measure for the quality of green innovation.

The estimation results using these alternative outcome variables are presented in columns (1)–(3) of table A4. Even after substituting for the independent variable, SCI continues to have a positive impact on both the quantity and quality of firms' green innovation.

B3. Using the Poisson model

Considering that the number of green invention patents constitutes count data, it is appropriate for estimation using the Poisson model. We use a fixed-effects Poisson model to estimate the effects of SCI on the quantity of firm green innovation, and the results are presented in column (4) of table A4. The estimation results from the Poisson model confirm that SCI can increase the quantity of firm green innovation.

Table A4. Re-estimating by replacing the dependent variable and using the Poisson model

	Replacement of the dependent variable			Poisson model
	(1)	(2)	(3)	(4)
Dependent variables	*Utility_num*	*Inno_q2*	*Mcite*	*Inno_num*
SCID	0.1043	0.0164	0.0371	0.8149
	(0.0296)	(0.0087)	(0.0212)	(0.1584)
Controls	Yes	Yes	Yes	Yes
R^2/*log_likelihood*	0.714	0.424	0.565	–27762.29
N	17,361	17,361	17,361	11,967

Notes: Inno_num is the natural logarithm of (a firm's annual number of green invention patents + 1), *Inno_q1* represents the quality of firm's green innovation, measured by the knowledge breadth of applied green inventions. *SCAID* is developed under the DID framework, for firms in the treatment group, it takes a value of 0 in the years prior to SCAI and 1 after, while firms in the control group take a value of 0 in all years. Robust standard errors clustered at the firm-level are shown in parentheses. Columns (1)–(4) present the estimation results of the DID model and column (5) presents the estimation results of the Poisson model. "Yes" indicates that all control variables in the baseline models are included.

B4. Including firms with state capital withdrawal after accepting SCI

In the baseline estimation, we exclude firms with state capital withdrawals after accepting SCI. Following Huang *et al.* (2017), we re-include such firms (a total of 364) in the sample and subsequently re-estimate the model. The results of this re-estimation are reported in columns (1) and (2) of table A5. Notably, the findings from the re-estimation closely align with those of the baseline estimation.

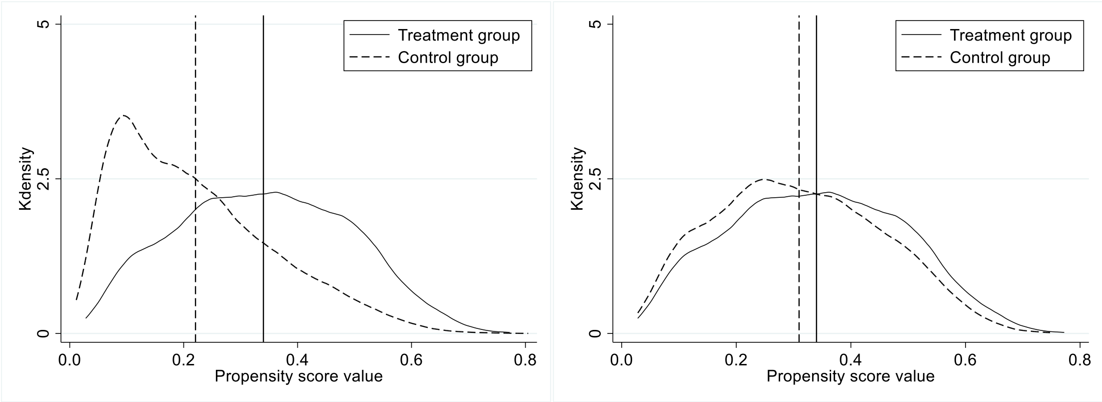
Table A5. Estimation results of other robustness test

	Including firms with state capital withdrawal after accepting SCI		Using samples after propensity score matching for estimation	
	(1)	(2)	(3)	(4)
Dependent variables	*Inno_num*	*Inno_q1*	*Inno_num*	*Inno_q1*
SCID	0.1213	0.0188	0.1572	0.0277
	(0.0294)	(0.0072)	(0.0443)	(0.0119)
Controls	Yes	Yes	Yes	Yes
R^2	0.745	0.436	0.835	0.593
N	18,749	18,749	4,521	4,521

Notes: Inno_num is the natural logarithm of (a firm's annual number of green invention patents + 1), *Inno_q1* represents the quality of firm's green innovation, measured by the knowledge breadth of applied green inventions. *SCAID* is developed under the DID framework, for firms in the treatment group, it takes a value of 0 in the years prior to SCAI and 1 after, while firms in the control group take a value of 0 in all years. Robust standard errors clustered at the firm level are in parentheses. "Yes" indicates that all control variables in the baseline models are included.

B5. Estimation using samples after propensity score matching (PSM)

As the SCI implementation process may be selective, this may introduce a selection bias in the regression estimates. To mitigate this issue, we apply PSM. Following Dong and Liu (2022), we conducted non-substitutable one-to-one yearly PSM utilizing all control variables in baseline model to match the treatment and control firms. Figure A2(a) and A2(b) illustrate the variations in the propensity score values for the treatment and control groups before and after matching. The results demonstrate a significant reduction in the disparities in the propensity score values between the two groups after matching. The estimation results using the matched firms are presented in columns (3) and (4) of table A5, and continue to support the positive effects of SCI on both the quantity and quality of firms' green innovation.



(a) Before matching

(b) After matching

Figure A2. Kernel density map before and after matching.
Panels (a) and (b) show the Kernel density map before and after matching, respectively.

B6. Estimation using the instrumental variable (IV) method

In addition to propensity score matching, the IV method can also solve the selectivity bias caused by the non-randomness of SCI, as well as the omitted variable bias and bidirectional causality issues. Some literature believes that one of the reasons for SCI is to control those key areas and strategic industries that are related to national security and the lifeline of the national economy (Chernykh, 2011). Therefore, we select whether a firm operates in a key sector or strategic industry as the instrumental variable (*IV_SCI*). Whether an industry is classified as a key sector or strategic industry is an exogenous variable for firms. Meanwhile, existing research has demonstrated that firms in these industries have a higher likelihood of being injected (Chernykh, 2011). Therefore, whether a firm belongs to a key sector and strategic industry may be an appropriate IV. Table A6 reports the results of the IV estimation.

The test results indicate that when *Inno_num* (*Inno_q1*) serves as the dependent variable, the chi-square statistic for the endogeneity test is 144.62 (47.50), with corresponding p-values of 0.000 (0.000), suggesting that SCI is highly likely an endogenous variable. Moreover, the

Kleibergen-Paap rk Wald F statistic for the weak instrument test is 210.088, exceeding the 10% significance level critical value of 16.38 in the Stock-Yogo test, which rejects the null hypothesis that the instrument is weak IV. The IV coefficient is 0.0196 and significant at the 1% level, indicating that firms in strategic industries have a higher probability of undergoing SCI. Additionally, in columns (2)–(3) of table A6, the coefficients of *SCID* are significantly positive, demonstrating that after mitigating endogeneity through the instrumental variable method, SCI still enhances the quantity and quality of firms' green innovation, thereby validating the robustness of the baseline regression results.

TableA6. Estimation results of the IV method

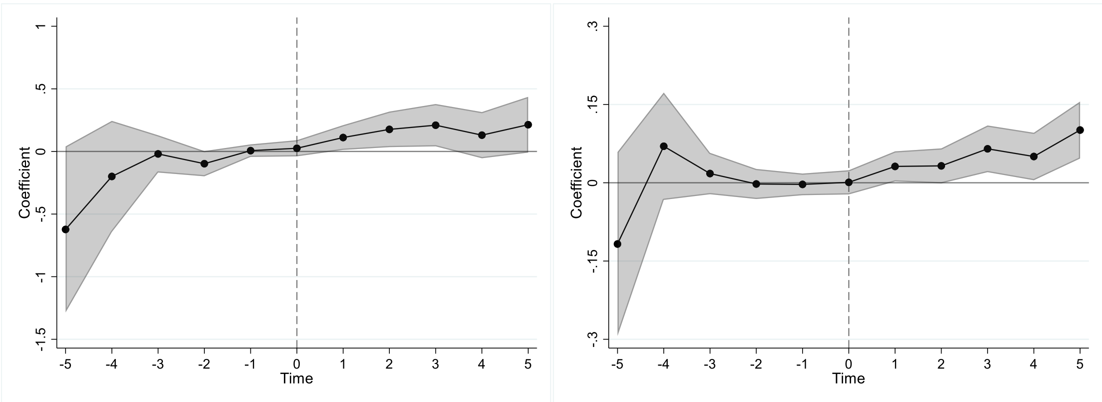
	First stage	Second stage	
	(1)	(2)	(3)
Dependent variables	*SCID*	*Inno_num*	*Inno_q1*
SCID		1.7631	0.3240
		(0.1977)	(0.0480)
IV_SCI	0.0196		
	(0.0025)		
Controls	Yes	Yes	Yes
R^2	0.0730	0.2743	0.0794
N	17,605	17,605	17,605

Notes: Inno_num is the natural logarithm of (a firm's annual number of green invention patents + 1), *Inno_q1* represents the quality of firm's green innovation, measured by the knowledge breadth of applied green inventions. *SCAID* is developed under the DID framework, for firms in the treatment group, it takes a value of 0 in the years prior to SCAI and 1 after, while firms in the control group take a value of 0 in all years. "Yes" indicates that all control variables in the baseline models are included.

B7. Eliminating bias caused by heterogeneous treatment effects

The application of a two-way fixed effects estimator for estimating staggered DID designs can introduce bias owing to heterogeneous treatment effects (Cengiz *et al.*, 2019; de Chaisemartin and D'Haultfœuille, 2020; Sun and Abraham, 2021). To mitigate the potential bias caused by heterogeneous treatment effects, we employed three new estimation methods for staggered

DID designs proposed by de Chaisemartin and D'Haultfœuille (2020), Sun and Abraham (2021), and Cengiz *et al.* (2019).[1] The estimation results using these three methods are presented in figures A3–A5, and they consistently confirm that SCI has a positive effect on both the quantity and quality of firms' green innovation.

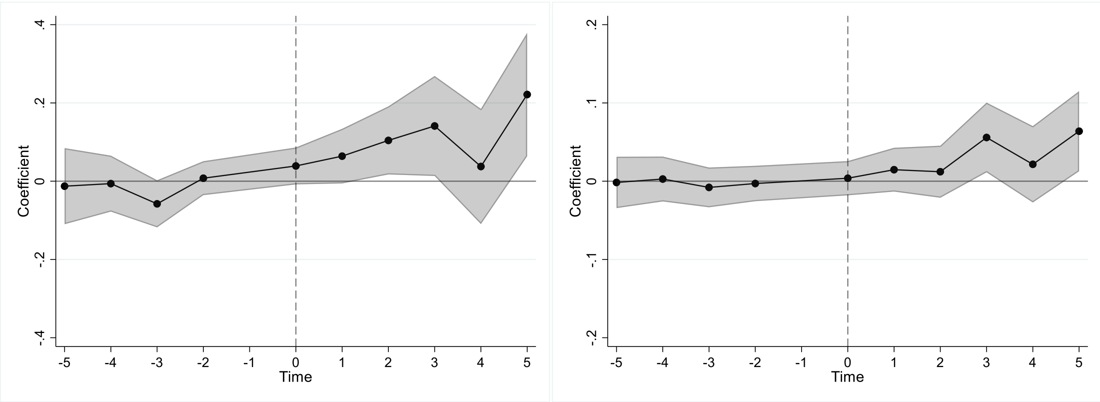


(a) Quantity of patent (b) Quality of patent

Figure A3. Results of using the method proposed by de Chaisemartin and D'Haultfœuille (2020).

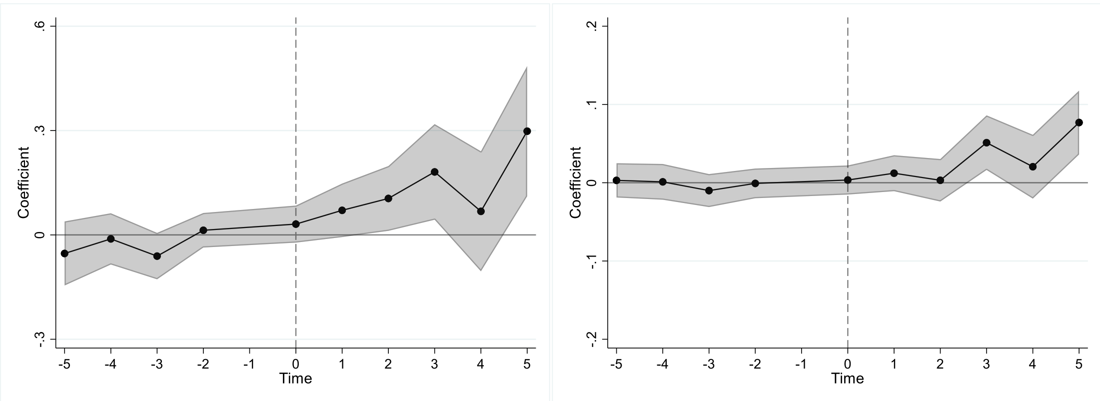
The horizontal coordinate represents the relative year before or after the year of implementation of SCI. Shaded areas represent 90% confidence intervals. Panels (a) and (b) show the estimation result using *Inno_num* and *Inno_q1* as the dependent variable, respectively. All control variables in the baseline model are included when conducting the estimation.

[1] The three estimation methods propose ways to address the bias caused by heterogeneous treatment effects. De Chaisemartin and D'Haultfœuille (2020) present a method for computing group-time treatment effects. It involves comparing the outcomes of firms that experience a change in treatment status to their counterfactual outcomes after accepting the treatment, thereby obtaining the instantaneous treatment effect. Then, the average treatment effect can be obtained by taking a weighted average. Similarly, Sun and Abraham (2021) employs a group-time treatment effect framework. They divide the treatment group G based on the treatment timing and the time periods T based on the calendar time to obtain the group-time groupings (G, T) and the average treatment effect on the treated, i.e., ATT (G, T), for each (G, T). Then, the average treatment effect is obtained by taking a weighted average of each ATT. Cengiz *et al.* (2019) proposed the stacked estimator. The main idea is to find the appropriate control group for each firm at each treatment time point (K) separately to form K traditional DIDs. These K datasets are then stacked together, and the OLS estimator is performed by further incorporating group-individual and group-time fixed effects, clustering the standard errors at the individual level.



(a) Quantity of patent (b) Quality of patent

Figure A4. Results of using the method proposed by Sun and Abraham (2021)**.**
The horizontal coordinate represents the relative year before or after the year of implementation of SCI. Shaded areas represent 90% confidence intervals. Panels (a) and (b) show the estimation result using *Inno_num* and *Inno_q1* as the dependent variable, respectively. All control variables in the baseline model are included when conducting the estimation.



(a) Quantity of patent (b) Quality of patent

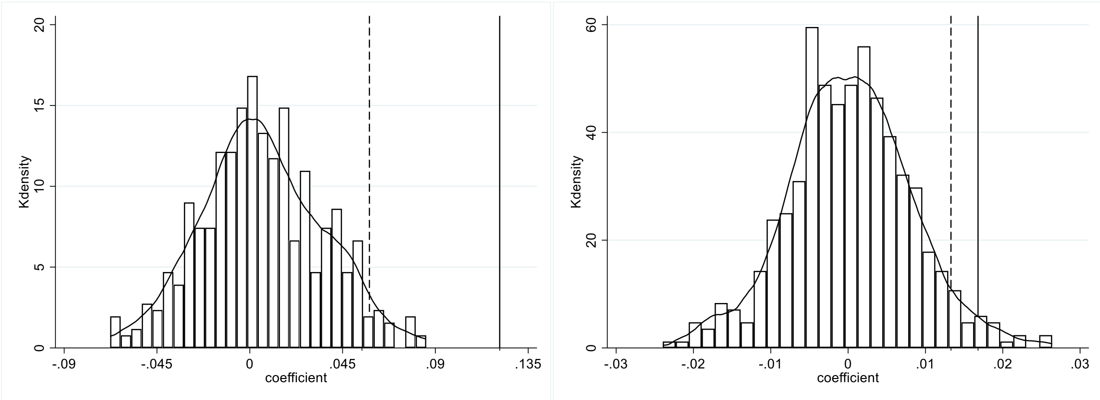
Figure A5. Results of using the method proposed by Cengiz *et al.* (2019).
The horizontal coordinate represents the relative year before or after the year of implementation of SCI. Shaded areas represent 90% confidence intervals. Panels (a) and (b) show the estimation result using *Inno_num* and *Inno_q1* as the dependent variable, respectively. All control variables in the baseline model are included when conducting the estimation.

B8. Placebo tests

A potential concern is that the observed positive effects of SCI on firms' green innovation in the baseline estimation may be accidental or influenced by unobserved factors. To address this, we conducted a placebo test. Here, we describe how it was conducted. (1) A random sample of 560 firms (the same number of firms accepted SCI in our sample) was drawn from a pool of 2,557 firms (the total number of firms in our sample) as the pseudo-treatment group. The remaining firms were assigned as the pseudo-control group to obtain the pseudo-treatment group dummy variable. (2) A random time point was selected for each firm in the pseudo-treatment group to serve as pseudo-treatment timing. The pseudo-treatment time dummy variable was generated based on the chosen pseudo-treatment timing. (3) The pseudo-SCI dummy variable was then generated by multiplying the pseudo-treatment group dummy variable with the pseudo-treatment time dummy variable. (4) The same model as in equation (A1) was applied to test the relationship between pseudo-SCI and firms' green innovation.

Figure A6 shows the distribution plot of the estimated coefficients obtained by repeating this process 500 times, with the coefficient from the baseline regression indicated by a solid vertical line. The vertical dashed line represents the 95th percentile of the estimated coefficients from 500 random simulations as a reference point.

The results show that regardless of the quantity (figure A6(a)) or quality (figure A6(b)) of green innovation as the outcome variable, the estimated coefficients from the 500 random samples mostly cluster around zero. Moreover, the coefficients from the baseline estimation (solid line) were larger than the simulated coefficients from the 95th percentile (dashed line). This indicates that the results of our baseline estimation are indeed driven by SCI and unlikely to be accidental or caused by other factors.



(a) Quantity of patents (b) Quality of patents

Figure A6. Results of placebo tests.

The coefficient denotes the effect of SCI on green innovation. Panels (a) and (b) show the estimation result using *Inno_num* and *Inno_q1* as the dependent variable, respectively. The vertical solid line is the estimated coefficient of the baseline regression, the vertical dashed line is the 95th percentile of the estimated coefficients estimated for a sample of 500 random samples. All control variables in the baseline model are included when conducting the estimation.

Appendix C. Robust test for section 5.1.4

Table A7. Estimation results of excluding firms with joint R&D

	(1)	(2)	(3)
Dependent variables	*R&D_exp*	*Inno_num*	*Inno_q1*
SCID	0.3099		
	(0.0482)		
R&D_exp		0.1195	0.0224
		(0.0144)	(0.0032)
Control varibales	Yes	Yes	Yes
R^2	13,971	13,971	13,971
N	0.879	0.692	0.422

Notes: Inno_num is the natural logarithm of (a firm's annual number of green invention patents + 1), *Inno_q1* represents the quality of firm's green innovation, measured by the knowledge breadth of applied green inventions. *SCAID* is developed under the DID framework, for firms in the treatment group, it takes a value of 0 in the years prior to SCAI and 1 after, while firms in the control group take a value of 0 in all years. Robust standard errors clustered at the firm level are in parentheses. "Yes" indicates that all control variables in the baseline models are included.

Appendix D. The estimation results of section 6

Table A8. The heterogeneity of SCAI's effects in the proportion of state-owned capital

	Share of state capital < 30%		Share of state capital ≥ 30%	
	(1)	(2)	(3)	(4)
Dependent variables	*Inno_num*	*Inno_q1*	*Inno_num*	*Inno_q1*
SCAID	0.1211	0.0177	0.3787	0.0406
	(0.0319)	(0.0080)	(0.1190)	(0.0235)
Control variables	Yes	Yes	Yes	Yes
R^2	0.751	0.442	0.748	0.441
N	17,069	17,069	13,829	13,829

Notes: Robust standard errors clustered at the firm level are in parentheses. "Yes" indicates that all control variables in the baseline models are included.

Table A9. The heterogeneity of SCAI's effects in the pollution intensity of industries

	Non-heavily polluting industries		Heavily polluting industries	
	(1)	(2)	(3)	(4)
Dependent variables:	*Inno_num*	*Inno_q1*	*Inno_num*	*Inno_q1*
SCAID	0.1067	0.0131	0.1703	0.0205
	(0.0245)	(0.0164)	(0.0331)	(0.0091)
Control variables	Yes	Yes	Yes	Yes
R^2	0.753	0.436	0.757	0.489
N	12,652	12,652	4,543	4,543

Notes: Robust standard errors clustered at the firm level are in parentheses. "Yes" indicates that all control variables in the baseline models are included.

Table A10. The heterogeneity of SCAI's effects in regional marketization level

	Low level of marketization		High level of marketization	
	(1)	(2)	(3)	(4)
Dependent variables:	*Inno_num*	*Inno_q1*	*Inno_num*	*Inno_q1*
SCAID	0.1748	0.0311	0.0877	0.0043
	(0.0461)	(0.0115)	(0.0420)	(0.0098)
Control variables	Yes	Yes	Yes	Yes
R^2	0.767	0.466	0.749	0.450
N	8,082	8,082	9,145	9,145

Notes: Robust standard errors clustered at the firm level are in parentheses. "Yes" indicates that all control variables in the baseline models are included.

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