ABSORPTIVE CAPACITY AND INNOVATION IN CHINA'S SEMICONDUCTOR INDUSTRY: ROLES OF INTERNATIONALIZATION, OWNERSHIP AND GOVERNMENT SUBSIDIES

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ABSTRACT
This study examines absorptive capacity and innovation among 166 Chinese listed semiconductor firms (2016-2024). The results from the two-way fixed-effects model indicate that firms with higher R&D intensity tend to exhibit stronger innovation performance ($\beta = 0.1723$, $p = 0.002$). State ownership strengthens this relationship, government subsidies weaken it, while internationalization has no significant moderating effect. Two-step System GMM estimates remain positive but statistically insignificant, providing no additional confirmation of the fixed-effects findings.
Keywords: Absorptive Capacity, Firm Innovation, Internationalization, State Ownership, Government Subsidies

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INTRODUCTION

Despite its large manufacturing base, China's semiconductor sector continues to rely on overseas suppliers for certain specialized technologies and production inputs. Semiconductor innovation requires cumulative expertise, high fixed investment, and coordination across design, fabrication, equipment, materials, and assembly and testing. International specialization provides access to knowledge but also exposes firms to disruptions and technological constraints(Semiconductor Industry Association, 2021; The Organisation for Economic Co-operation and Development, 2025). Upgrading therefore depends partly on firms' ability to recognize, assimilate, and apply external knowledge (Cohen & Levinthal, 1990; Lim, 2009).

Industrial policies seek to strengthen these capabilities through research support, tax preferences, financing, and talent development. Made in China 2025 identifies integrated circuits and related equipment as priorities, while subsequent policies differentiate support by enterprise and project characteristics(State Council of the People's Republic of China, 2015). These measures may ease financing constraints, but greater public support does not necessarily increase the productivity of internal R&D (Wen & Zhao, 2021; Xu & Naysary, 2021).

This study examines whether R&D-based absorptive capacity is associated with innovation among Chinese A-share semiconductor firms and whether the association varies with internationalization, state ownership, and technology-innovation subsidies. International exposure may expand access to knowledge; ownership can alter investment horizons and access to research infrastructure; and subsidies may complement or substitute for privately financed effort. These conditions are examined through separate interaction models within a common empirical framework.

The source panel contains 1,085 firm-year observations for 189 firms over 2015-2024. The common estimation sample comprises 753 observations from 166 firms over 2016-2024. Firm and year fixed-effects models are supplemented by measurement and coverage checks and dynamic panel estimates. The contribution is to distinguish conditional R&D-innovation associations from causal claims and to show how findings depend on accounting proxies, record coverage, and identifying assumptions.

LITERATURE REVIEWS

Absorptive Capacity and Innovation

According to Cohen and Levinthal (1990), absorptive capacity enables firms to identify useful knowledge from outside the organization, develop an understanding of it, and put it to commercial use(Cohen & Levinthal, 1990). Zahra and George (2002) conceptualize absorptive capacity as two components: potential capacity concerns acquiring and assimilating knowledge, while realized capacity concerns transforming and exploiting it. This distinction suggests that obtaining knowledge alone is insufficient for innovation; firms must draw on established practices and accumulated expertise to put that knowledge into use (Zahra & George, 2002). External search varies in scope, depth, and orientation, which can influence innovative performance (Chen et al., 2011).

Internal R&D develops technical expertise and supports learning from suppliers, universities, alliances, and skilled labor networks. In semiconductors, absorptive capacity helps firms integrate knowledge across specialized production stages (Lim, 2009). Catch-up is nevertheless constrained by cumulative learning, rapid technological change, and capital requirements (Rho et al., 2015). R&D intensity is consequently a useful observable input into absorptive capacity, although it cannot represent all of its organizational dimensions (Flatten et al., 2011).

Internationalization Ownership and Subsidies

Internationalization can expose firms to foreign customers, suppliers, technologies, and competitive pressures, creating opportunities for learning (Love & Roper, 2015; Songlin & Chao, 2017). Such opportunities may complement absorptive capacity, but foreign expansion also increases coordination costs and organizational complexity. The relationship is therefore contingent on firms' resources and international experience rather than uniformly positive (Du et al., 2023). Overseas revenue measures market exposure but does not directly capture research partnerships or the quality of knowledge acquired abroad.

Ownership influences governance, financing, and access to complementary resources. Private ownership may strengthen market discipline(Shleifer, 1998), while financing constraints can limit sustained R&D investment (Rui, 2019). State ownership may provide patient capital, research infrastructure, and participation in strategic projects, although administrative inefficiencies and agency problems can offset these advantages (Xu et al., 2025). In a capital-intensive sector, the resource advantages of state ownership motivate a positive moderation hypothesis without implying that SOEs are universally more innovative.

Subsidies can reduce the cost of experimentation and relax financing constraints (Howell & T., 2017). Their effects may nevertheless depend on intensity and incentives. Public funding can replace private expenditure, encourage grant seeking, or support projects beyond firms' implementation capacity (Jia-yun, 2015; Xu & Naysary, 2021). Industry-university-research cooperation also depends on the interaction between public support and technological absorptive capacity (Dong-mei, 2016). These competing mechanisms motivate examining subsidy intensity as a moderator rather than assuming a uniformly beneficial direct effect.

Research Gap and Hypotheses

Existing work establishes the importance of technological learning and external resources, but semiconductor evidence includes substantial case-based and sectoral analysis(Lim, 2009; Rho et al., 2015). This study adds firm-level panel evidence and compares three conditions under which internal R&D may translate into recorded innovation. It tests the following hypotheses:

H1: Greater absorptive capacity corresponds to better innovation performance in Chinese semiconductor firms.

H2: Internationalization strengthens the positive relationship between absorptive capacity and firm innovation.

H3: The innovation benefits associated with absorptive capacity are greater for state-owned semiconductor firms than for non-state-owned firms.

H4: As technology-innovation subsidy intensity increases, the positive association between absorptive capacity and innovation becomes weaker.

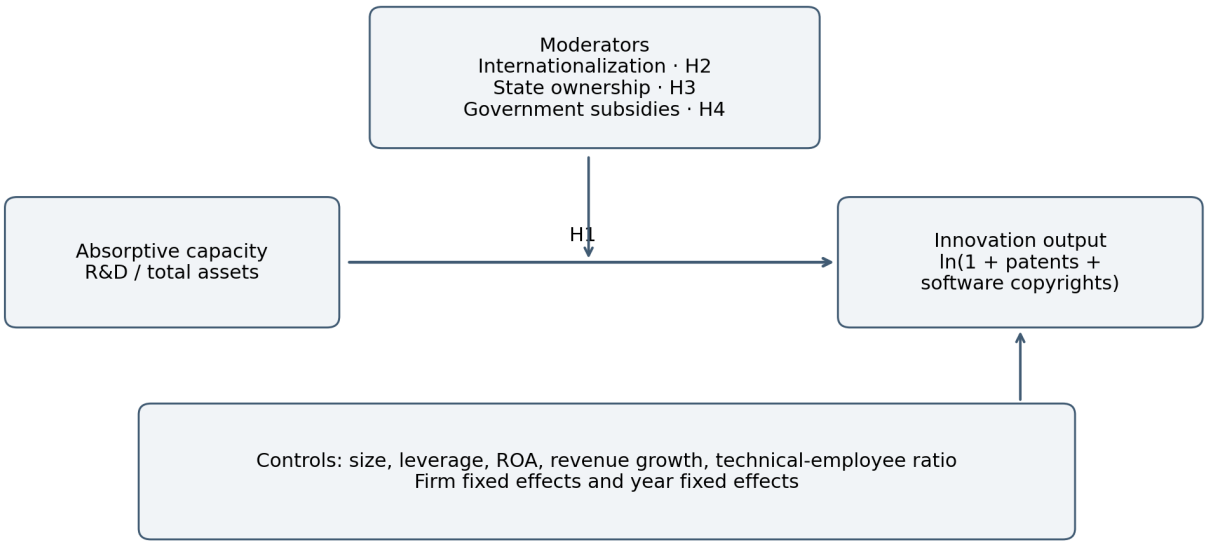

Figure 1 Conceptual Framework

RESEARCH METHODOLOGY

Data and Sample

Chinese A-share semiconductor firms are identified using Wind industry classifications and matched to CCERDATA. Annual reports, CCERDATA, and Wind provide innovation, financial, ownership, employment, and subsidy information. Differences in listing dates and data availability generate an unbalanced panel. The 2015-2024 source data contain 1,085 observations from 189 firms; complete-case screening for baseline and moderation regressors produces 753 observations from 166 firms over 2016-2024.

Model Specification, Variable Definition, and Measurement

The main specifications are linear two-way fixed-effects models that identify associations from changes within firms over time. Firm fixed effects absorb time-invariant firm characteristics, while year effects capture shocks common to all firms in a given year. Standard errors are clustered at the firm level. The baseline models estimate the direct relationship between absorptive capacity and innovation; separate interaction specifications then test whether that relationship differs with internationalization, state ownership, or government subsidies.

Model Specification

$$lninno_{it} = \beta_0 + \beta_1 absorb_{it} + \beta_2 inter_{it} + \beta_3 subsidy_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

In the displayed baseline equation, lninno is logged innovation, absorb is percentage-unit R&D intensity, inter is the overseas-revenue ratio, and subsidy is percentage-unit subsidy intensity. X contains firm size, leverage, ROA, revenue growth, and the technical-employee ratio; $\mu_i$and λ_t denote firm and year effects. Model 1 includes absorb and the fixed effects; Model 2 adds X; Model 3 adds inter and subsidy. Separate models add absorb × inter, absorb × SOE, or absorb × subsidy, together with the corresponding main effects. Internationalization remains a decimal ratio and SOE is coded 0/1. Continuous variables entering interactions are mean-centered over the common sample. Time-invariant ownership main effects are absorbed by firm effects, while interactions with time-varying R&D intensity remain estimable.

The definitions and measurement approaches for the variables are presented below:

Table 1 Variables Definition

Category	Variable	Definition	Measurement
Dependent variable	lninno	Firm innovation output	ln(1 + patents + software copyrights); missing component counts are coded as zero
Core explanatory variable	absorb (%)	Absorptive capacity	100 × R&D expenditure / total assets
Control variable	lnsize	Firm size	ln(1+total assets)
Control variable	leverage	Financial leverage	Total liabilities / total assets
Control variable	roa	Profitability	Net income / total assets
Control variable	growth	Revenue growth	Annual growth rate of operating revenue
Moderator	inter	Internationalization	Overseas revenue / operating revenue
Moderator	soe	State ownership	1 for state-owned controlling shareholder; 0 otherwise
Moderator	subsidy (%)	Technology-innovation subsidy intensity	100 × technology-innovation subsidy amount / total assets
Control variable	techratio	Technical workforce	Technical employees / total employees
Alternative measure	$inter_d$	Internationalization dummy	1 if overseas revenue is positive; 0 otherwise
Alternative measure	R&D/revenue (%)	Alternative absorptive capacity	100 × R&D expenditure / operating revenue

RESEARCH RESULTS

Descriptive Statistics

The source dataset contains 1,085 firm-year observations for 189 firms over 2015-2024. Requiring non-missing values for the baseline and moderation regressors yields a common sample of 753 observations from 166 firms over 2016-2024. This is a complete-case sample for those regressors, not a sample with fully observed intellectual-property and subsidy records; the missing-data rules described above still apply.

In the common estimation sample, lninno has a mean of 3.516 and a standard deviation of 2.271, ranging from 0 to 8.467. The wide dispersion indicates substantial heterogeneity in firms' combined patent and software-copyright output. The unlogged innovation count is strongly right-skewed, supporting the logarithmic transformation used in the baseline model.

Absorptive capacity, expressed in percentage units, has a mean of 4.614 and a standard deviation of 4.182, ranging from 0.184 to 26.395. Thus, the average firm allocates R&D expenditure equivalent to approximately 4.6% of total assets, although the upper tail invests considerably more intensively.

The mean log of total assets is 22.433, while leverage averages 0.365. Internationalization averages 0.291, implying that overseas revenue accounts for approximately 29.1% of operating revenue in the estimation sample. The mean technical-employee ratio is 0.318, indicating material variation in human-capital composition across firms.

ROA averages 0.088, with a range from −1.204 to 0.919. Revenue growth is strongly right-skewed, with a mean of 0.306 and a maximum of 58.842. These extreme values motivate the

winsorized sensitivity analysis. Firm-clustered inference is supported separately by the serial-correlation and heteroskedasticity diagnostics.

Subsidy intensity, expressed in percentage units, has a mean of 0.001823 and a standard deviation of 0.009476. Its median is zero and its maximum is 0.137482. The mean therefore corresponds to subsidy amounts of approximately 0.001823% of total assets. The highly skewed distribution partly reflects the assumed-zero treatment of unmatched records. Consequently, zero values cannot uniformly be interpreted as confirmed absence of subsidies. The within-firm standard deviation of R&D intensity is 1.279 percentage points. Fixed-effects estimates use this variation over time rather than cross-sectional differences alone.

Table 2 Descriptive Statistics

Variable	N	Mean	SD	Min	Max
lninno	753	3.516	2.271	0	8.467
Absorb (%)	753	4.614	4.182	0.184	26.395
inter	753	0.291	0.262	0	0.989
Subsidy (%)	753	0.001823	0.009476	0	0.137482
lnsize	753	22.433	1.144	19.007	26.548
leverage	753	0.365	0.206	0.018	0.919
roa	753	0.088	0.165	−1.204	0.919
growth	753	0.306	2.190	−0.971	58.842
techratio	753	0.318	0.224	0	0.924

Baseline Results

Table 3 reports three baseline models on the same 753 observations from 166 firms. Model 1 includes absorptive capacity plus firm and year fixed effects. Model 2 adds size, leverage, ROA, revenue growth, and the technical-employee ratio. Model 3 also includes internationalization and asset-scaled subsidy intensity. The within R-squared rises from 0.275 to 0.298 as covariates are added.

Table 3 Baseline Fixed Effects Results

Variable	Model 1	Model 2	Model 3
Absorptive capacity (%)	0.1501**(0.0578)	0.1724***(0.0570)	0.1723***(0.0561)
Internationalization	—	—	0.228(0.968)
Subsidy / assets (%)	—	—	−11.5763*(6.9679)
Firm size	—	0.385*(0.226)	0.366*(0.211)
Leverage	—	0.676(0.777)	0.719(0.774)
ROA	—	1.648**(0.705)	1.699**(0.689)
Revenue growth	—	0.031***(0.007)	0.031***(0.008)
Technical employee ratio	—	0.388(1.087)	0.531(1.088)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	753	753	753
Firms	166	166	166
Within R-squared	0.275	0.295	0.298

Notes: Firm and year fixed effects are included in all models. Firm age is excluded. Firm-clustered standard errors appear in parentheses. The reference year is 2016. Absorptive capacity and subsidy intensity equal their respective asset-scaled ratios multiplied by 100; a

one-unit increase denotes one percentage point. Other controls retain their original units. * p < 0.10, ** p < 0.05, *** p < 0.01.

Across the three fixed-effects specifications, the coefficient on absorptive capacity is positive and statistically significant. In the full model, it is 0.1723 (p = 0.002; 95% CI 0.0615-0.2831). A one-percentage-point increase in R&D expenditure relative to total assets is associated with a 0.1723 increase in ln(1 + recorded innovation count), conditional on the included covariates and fixed effects. These estimates support H1 within the static fixed-effects framework; the dynamic results below qualify their interpretation.

In the full model, ROA is positive and significant (β = 1.699, p = 0.015), as is revenue growth (β = 0.031, p < 0.001). Firm size is positive at the 10% level (β = 0.366, p = 0.085), while subsidy intensity is negative at that level (β = −11.5763, p = 0.099). Leverage, the technical-employee ratio, and internationalization are not significant at the 5% level. The interaction models examine whether contextual variables change the absorptive-capacity slope.

Moderating Effects

Table 4 Moderating Effects

Interaction	Coefficient	Robust SE	t	p-value	Hypothesis assessment
Absorb × Internationalization	−0.0691	0.1915	−0.36	0.719	Not supported
Absorb × SOE	0.2897	0.1179	2.46	0.015	Supported
Absorb × Subsidy/assets	−4.4810	1.0313	−4.34	<0.001	Supported in main sample

Notes: Each row reports an interaction from a separate model with firm and year fixed effects and firm-clustered standard errors. Absorptive capacity and subsidy intensity are in percentage units. Internationalization remains a 0-1 ratio and SOE remains a 0/1 indicator. * p < 0.10, ** p < 0.05, *** p < 0.01.

The interaction between absorptive capacity and internationalization is negative but imprecisely estimated (β = −0.0691, p = 0.719). Its wide confidence interval crosses zero by a substantial margin, so the data do not support the claim that foreign-market exposure systematically strengthens the innovation return to absorptive capacity. H2 is therefore not supported. One plausible interpretation is that overseas exposure creates access to knowledge but also raises coordination and adaptation costs; the average net moderation effect may consequently be weak across heterogeneous firms.

The ownership interaction is positive and significant (β = 0.2897, SE = 0.1179, p = 0.015). Since SOE equals one for state-controlled firms, this coefficient indicates that a one-percentage-point increase in R&D intensity is associated with a 0.2897 greater increase in logged innovation among SOEs than among non-SOEs, supporting H3. The full-sample interaction directly tests this slope difference using 753 observations from 166 firms. It does not depend on comparing significance levels across small ownership subsamples. Patient capital, shared research infrastructure, and participation in strategic projects are possible explanations.

The interaction between absorptive capacity and asset-scaled subsidy intensity is negative and statistically significant (β = −4.4810, SE = 1.0313, p < 0.001), supporting H4 in the main specification. Both variables are expressed in percentage units. An increase of 0.01 percentage points in subsidy intensity is associated with a 0.04481 reduction in the predicted change in logged innovation per one-percentage-point increase in R&D intensity. This indicates a weaker conditional association at higher subsidy intensity.

Dynamic Panel Estimates and Endogeneity

Table 5 Dynamic Panel GMM Estimates

Variable / diagnostic	**(1) SystemLags 2**	**(2) SystemLags 2-3**	**(3) DifferenceLags 2-3**
R&D intensity (%)	0.0188(0.0759)	0.0925(0.0809)	0.3791(0.3331)
Lagged innovation	0.3394***(0.1198)	0.3096***(0.1178)	0.2651(0.2636)
R&D coefficient p-value	0.804	0.254	0.257
Controls and year effects	Yes	Yes	Yes
Observations	753	753	581
Firms	166	166	140
Instruments	27	36	26
AR(1) p-value	0.054	<0.001	0.082
AR(2) p-value	0.141	0.426	0.615
Hansen p-value	0.480	0.407	0.834
Sargan p-value	0.372	0.313	0.770
Level-instrument difference-in-Hansen p-value	0.480	0.129	Not applicable

Notes: Two-step estimates with Windmeijer-corrected robust standard errors and a small-sample adjustment. All models include year indicators and lagged innovation. R&D intensity, internationalization, subsidy intensity, and the five controls are treated as potentially endogenous. Instrument sets are collapsed. Columns (1) and (2) use System GMM; column (3) uses Difference GMM. Parentheses contain standard errors. AR tests concern first-differenced errors. Non-rejection of Hansen tests does not establish instrument validity. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Innovation may influence subsequent R&D spending, while unobserved shocks can affect both variables. To address this concern directly, the dynamic specification adds lagged innovation: $y_{it} = \rho y_{i,t-1} + \beta A_{it} + \delta I_{it} + \theta S_{it} + \gamma' X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}$, where A is R&D intensity, I is internationalization, S is subsidy intensity, and X contains the five controls. Two-step System GMM uses second lags, or second and third lags, of innovation and the contemporaneous firm-level regressors as instruments for differenced equations. Lagged differences instrument the level equations. Instrument matrices are collapsed to limit proliferation. These additional level moments require restrictions on initial conditions and the relationship between changes in the variables and firm effects (Roodman, 2009). Difference GMM provides a comparison without the additional level equations.

Table 5 reports all three specifications. The System GMM absorptive-capacity coefficients are 0.0188 ($p = 0.804$) and 0.0925 ($p = 0.254$), using 27 and 36 instruments, respectively, for 166 firms and 753 observations. Lagged innovation is positive and significant in both models (0.3394, $p = 0.005$; 0.3096, $p = 0.009$). AR(2) p-values are 0.141 and 0.426, and Hansen p-values are 0.480 and 0.407. Difference-in-Hansen tests for the additional level instruments yield $p = 0.480$ and $p = 0.129$. These tests do not reject the stated restrictions at the 5% level, but do not establish their validity or rule out weak instruments.

Difference GMM yields a positive but imprecise absorptive-capacity coefficient (0.3791, $p = 0.257$; 581 observations, 140 firms). Its AR(2) and Hansen p-values are 0.615 and 0.834. The overall robust F statistic is unavailable, so this specification is treated as a limited sensitivity comparison. AR(1) is significant in the second System GMM model ($p < 0.001$), but only at the 10% level in the first System GMM and Difference GMM models ($p = 0.054$ and 0.082). The diagnostics therefore should not be summarized as uniformly conclusive.

Supplementary fixed-effects timing checks remain positive when R&D intensity is lagged one year ($\beta = 0.0793$, SE = 0.0350, $p = 0.025$; 753 observations, 166 firms) or two years ($\beta = 0.1302$, SE = 0.0449, $p = 0.004$; 619 observations, 141 firms). These regressions establish temporal ordering but do not eliminate feedback or omitted-variable bias. Taken together, the dynamic estimates provide no statistically significant confirmation of a positive absorptive-capacity effect. Their confidence intervals also do not establish that the effect is zero.

DISCUSSION AND CONCLUSION

The static fixed-effects models show a positive absorptive-capacity association, a positive SOE interaction, a negative subsidy interaction, and no significant internationalization interaction. However, the absorptive-capacity coefficient is not significant in either System GMM specification or in Difference GMM. Measurement and coverage also matter: revenue-scaled R&D is insignificant, complete-IP-record estimates are less precise, and the subsidy interaction is not significant among matched subsidy records. The evidence therefore supports conditional patterns in the fixed-effects models, with limited support for a causal interpretation.

The positive fixed-effects association is consistent with the view that internal R&D resources help firms use external knowledge. However, R&D intensity does not directly measure learning routines, and the dynamic estimates do not establish a statistically significant positive R&D effect. The findings therefore provide qualified evidence consistent with absorptive-capacity theory, rather than a direct test of its organizational mechanisms.

The interaction estimates suggest that the R&D-innovation association differs across ownership and subsidy conditions. Financing horizons, access to research infrastructure, and project-selection incentives are possible explanations. An insignificant internationalization interaction also does not establish that foreign knowledge linkages are unimportant; overseas revenue is an incomplete measure of those linkages.

The findings motivate evaluating innovation support against technological progress and commercialization rather than expenditure alone. Technological milestones, follow-on investment, and collaboration outcomes could inform such evaluation. The positive SOE interaction motivates further examination of access to patient capital and shared research infrastructure. Similarly, the absence of a significant internationalization interaction suggests that overseas revenue alone may be insufficient for assessing knowledge acquisition. Policy evaluations should examine these mechanisms directly before recommending differentiated support.

Limitations and Future Research

Several limitations should be considered. First, patent and software-copyright counts do not fully reflect technological significance or commercial value. Future research could examine patent citations, the proportion of invention patents, patent claims, or new-product revenue. Second, missing intellectual-property counts are coded as zero. The absorptive-capacity estimate remains positive in the complete-record sample but is not significant at the 5% level, so uncertainty about non-disclosure remains relevant. Unmatched subsidy records are also treated as assumed zeros in the main analysis. The insignificant subsidy interaction in the matched-record sample limits the strength of the moderation conclusion.

Third, absorptive capacity is multidimensional, while R&D intensity captures only one input. Survey-based measures of knowledge acquisition, assimilation, transformation, and exploitation would complement accounting data. Fourth, GMM relies on lag-instrument and initial-condition assumptions that diagnostic non-rejection cannot verify. Its insignificant absorptive-capacity coefficients leave causal conclusions unresolved. External instruments or credible policy-based designs could provide stronger identification when their exclusion restrictions or identifying assumptions can be justified.

Finally, the source data contain 189 firms, while the common regression sample comprises 166 firms and 753 observations over 2016-2024. Findings therefore apply to firms meeting the data-availability requirements. The large negative 2024 year coefficient may reflect changes in innovation or reporting coverage; the year effect alone cannot distinguish these explanations. Ownership heterogeneity is assessed within the full-sample interaction model, although the relatively limited representation of SOEs remains a constraint on generalization.

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