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State Capital Participation and AI Transformation in Private Firms: Evidence from Persistent Minority State Ownership in China

liangliang wang
Wenzhou Business College
xiaodong dou
dou10740185300163.com

Zhejiang University

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State Capital Participation and AI Transformation in Private Firms

Abstract

This study examines minority state ownership and AI transformation in privately controlled Chinese A-share firms during 2010–2025 using CSMAR data. Persistent State Entry begins in the second of two consecutive years with aggregate state ownership of at least 5%. AI transformation is measured by the number of distinct AI terms in MD&A (AI Breadth) and log one plus granted group-level AI invention patents (AI Patents). Firm, industry-by-year, and province-by-year fixed-effects estimates show positive associations with both outcomes, with stronger statistical support for patents. Results are consistent with R&D, technical staffing, knowledge assets, and financing channels, and associations are more favorable among firms with stronger pre-confirmation technological foundations and in competitive industries. Because treatment marks persistence confirmation rather than initial entry, the estimates are associational and do not identify a first-exposure shock.

Keywords: state capital participation; private firms; artificial intelligence; innovation; reverse mixed-ownership reform
JEL classification: G34; O32; O33; P31

1. Introduction

AI transformation requires sustained R&D, technical workers, data infrastructure, and tolerance for uncertain returns rather than simply acquiring standardized software. Research based on AI employment and occupational exposure suggests that AI outcomes depend on firms' existing skills and capabilities (Acemoglu et al., 2022; Babina et al., 2024; Felten et al., 2021). This makes AI a useful setting for examining how ownership arrangements shape long-horizon investment.

Chinese private firms combine flexible market-oriented decision-making with potential disadvantages in long-term financing, external credibility, and access to specialized labor. Minority state shareholdings may supply financial and network resources without transferring ultimate control. Prior studies associate such participation with innovation, digital transformation, risk taking, and strategic decisions (Chen et al., 2024; Jin et al., 2025; Li et al., 2024; Ni et al., 2026; Xu et al., 2025; Yang et al., 2026).

The implications for AI remain ambiguous. State-linked capital can facilitate experimentation and technical recruitment, whereas stronger monitoring and stability preferences may constrain risky projects. Prior research reports both favorable innovation outcomes and reduced strategic change; corporate disclosure may also diverge from technological activity (Jin et al., 2025; Li et al., 2024; Yang et al., 2026). We therefore examine when minority state participation accompanies AI capability building.

Using a 2010–2025 CSMAR panel of privately controlled A-share firms, we define persistence confirmation as the second consecutive year with at least 5% aggregate state ownership. We study distinct AI terms disclosed in MD&A (AI Breadth) and granted group-level AI invention patents (AI Patents), controlling for firm, industry-by-year, and province-by-year fixed effects. Confirmation is not equivalent to first state-capital exposure.

Persistent State Entry is positively associated with AI Breadth (0.268, significant at 10%) and AI Patents (0.059, significant at 5%) in the full model. Patent differences emerge more clearly at longer post-confirmation horizons. Results are consistent with R&D inputs, technical personnel, intangible assets, and financing channels. Effects are more favorable among firms with stronger pre-confirmation digital and R&D foundations and in more competitive industries.

We contribute by extending minority-state-ownership research to AI capabilities, distinguishing AI disclosure breadth from patented output, and identifying complementarities with existing technological foundations and competitive pressure. These findings suggest a conditional resource-and-governance role rather than a universal effect. The following sections set out the hypotheses, design, evidence, and implications.

2. Literature Review and Hypothesis Development

2.1 Economic Consequences of State Capital Participation in Private Firms

Reverse mixed-ownership reform includes state investment in private firms without a transfer of ultimate control. Minority state participation may influence corporate decisions despite limited voting power. Existing studies connect it to green innovation, risk taking, digitalization, labor investment, strategic change, and innovation (Chen et al., 2024; Jin et al., 2025; Ni et al., 2026; Xu et al., 2023, 2025; Yang et al., 2026).

Resource access and governance pressures create opposing predictions. State shareholders may improve legitimacy, finance, and policy networks while raising monitoring and stability demands. Political connections and industrial support can provide resources without comparable improvements in innovation quality or productivity (Cheng et al., 2024; Han et al., 2024; Li & Branstetter, 2024). Li et al. (2024) report lower digital disclosure but higher digital innovation, while Yang et al. (2026) find less strategic change. The balance depends on firms' capabilities and investment needs.

2.2 Measuring Corporate AI Transformation and Its Resource Base

Corporate AI has been measured through occupational exposure (Felten et al., 2021), job vacancies (Alekseeva et al., 2021; Acemoglu et al., 2022), resumes (Babina et al., 2024), disclosures, and patents. These indicators reflect different stages of AI adoption and should not be treated as interchangeable.

Annual-report AI language indicates managerial attention and disclosed technological scope, not necessarily implementation. Patents reflect a narrower, examined technological output (Kelly et al., 2021; Zhai & Liu, 2023), although grant dates lag inventive activity. We therefore use both disclosure breadth and granted invention patents.

2.3 State Capital Participation and AI Transformation

AI projects need continued R&D, technical workers, and complementary infrastructure. Resource-dependence theory suggests minority state shareholders may facilitate external financing and networks (Pfeffer & Salancik, 1978), while the resource-based view predicts that benefits depend on firm-specific capabilities (Barney, 1991). Evidence on innovation inputs and strategic hiring supports this possibility (Jin et al., 2025; Ni et al., 2026; Xu et al., 2025), but industrial-policy research cautions that added resources need not produce upgrading (Li & Branstetter, 2024).

AI Breadth may respond when firms expand technological exploration, whereas patents appear after invention, filing, examination, and grant. Comparing the two outcomes helps distinguish changes in reported engagement from technological output and potential differences in timing.

H1a. Persistent minority participation by state capital is positively associated with the breadth of AI-related technological engagement in privately controlled firms.

H1b. Persistent minority participation by state capital is positively associated with AI invention-patent output in privately controlled firms.

2.4 Mechanisms and Boundary Conditions

2.4.1 R&D Resources, Technical Personnel, and Knowledge-Asset Accumulation

AI capability depends on accumulated research inputs, specialized personnel, and knowledge assets, not just cash. State participation has been linked to R&D investment, hiring, and innovation resources (Ni et al., 2026; Xue et al., 2026). Greater expenditure can fund experimentation; technical staff facilitate absorption of knowledge; and intangible assets reflect accumulated software and intellectual property. We test these resource channels.

H2. The positive relationship between persistent state capital participation and AI transformation is partly reflected in greater R&D resources, technical personnel, and knowledge-asset accumulation.

2.4.2 Financing Constraints and AI Technological Output

Patentable AI projects require financing through development, filing, and examination. State shareholders may improve creditworthiness, lender relationships, or long-horizon funding. Prior studies link state equity participation to improved financing conditions and digital transformation (Chen et al., 2024; Jin et al., 2025; Xu et al., 2025). Financing constraints may therefore be especially relevant to patent output.

H3. The positive relationship between persistent state capital participation and AI patent output is partly reflected in an easing of financing constraints.

2.4.3 Pre-Confirmation Technological Foundations and Absorptive Capacity

Existing technological capabilities determine how effectively external resources support AI. Prior R&D knowledge improves firms' absorptive capacity (Cohen & Levinthal, 1990), while digital systems provide infrastructure for AI deployment. We measure these characteristics before persistence confirmation, not necessarily before first exposure: the first qualifying ownership year may already precede confirmation.

H4. The positive relationship between persistent state capital participation and AI transformation is stronger for firms with stronger digital and R&D foundations measured before persistence confirmation and for firms in high-technology industries.

2.4.4 Industry Competition

Competition raises the incentive to improve efficiency and differentiate products. Accordingly, state-linked resources may be more likely to support AI upgrading where competitive pressure is stronger. Prior evidence shows that institutional ties and innovation outcomes depend on industry conditions (Zhong & Zheng, 2025; Zhou et al., 2024).

H5. The positive relationship between persistent state capital participation and AI transformation is stronger in more competitive industries.

3. Research Design

3.1 Sample and Data

We construct an unbalanced 2010–2025 panel of privately controlled Chinese A-share listed firms using only CSMAR data on ownership, accounting, governance, MD&A text, and patents. The firm-year is the unit of observation. Firms with state ownership already present at sample entry are excluded because entry timing cannot be identified; observations after a transfer to state ultimate control are also excluded. Before complete-case restrictions, the sample contains 25,275 firm-years for 3,090 firms, including 146 firms that satisfy the persistent 5% rule.

Following prior studies of minority state shareholding (Chen et al., 2024; Jin et al., 2025; Li et al., 2024; Xu et al., 2025), continuous variables are winsorized at 1% and 99%; indicator and timing variables are unchanged, and missing data are not imputed. The C3 complete-case sample has 18,866 observations before singleton removal and 18,657 afterward. All baseline specifications use the final 18,657 observations.

3.2 Variable Construction

3.2.1 Persistent State Capital Participation

Persistent State Entry equals one from the second consecutive calendar year in which aggregate state ownership reaches at least 5%, remaining one thereafter; never-confirmed firms remain zero (Chen et al., 2024; Mao & Quan, 2025; Zhang et al., 2023). This rule excludes transient holdings but dates confirmation, not initial entry. The year $t = -1$ may already include the first qualifying shareholding. Consequently, the treatment indicator represents outcomes after confirmation of a sustained ownership episode rather than actual ownership in every subsequent year.

3.2.2 AI Transformation Outcomes

AI Breadth counts distinct AI-related terms with positive frequency in firm-year CSMAR MD&A text. Unlike total keyword frequency, repetition of one term does not increase the measure. It captures disclosed technological scope, not verified use. Disclosure measures complement employment-based AI indicators and text-based measures used elsewhere (Babina et al., 2024; Chen et al., 2025; Cheng et al., 2026; Felten et al., 2021).

AI Patents is ln[1 + (RInvig + RInvjg)], using CSMAR grants of AI invention patents for listed-firm groups (Kelly et al., 2021; Zhai & Liu, 2023). Patent examination supplies external validation, but grant years may lag invention. The two outcomes distinguish disclosed engagement from patented technological output.

3.2.3 Control Variables

Control variables are organized into predetermined nested sets rather than selected on the basis of statistical significance. C1 contains firm size, leverage, return on assets, sales growth, and operating cash flow. C2 adds Tobin's Q, asset turnover, fixed-asset intensity, a loss indicator, and listing age. C3 further includes board size, the proportion of independent directors, CEO-chair duality, ownership of the largest shareholder, Big Four auditor status, and industry concentration. All variables are drawn from the CSMAR dataset and are defined in Table 1. R&D variables, financing constraints, and intangible assets are excluded from the baseline control vector because they are examined as potential channels through which state participation may be associated with AI outcomes.

3.2.4 Mechanism and Heterogeneity Variables

The mechanism variables capture resource inputs, knowledge-asset accumulation, and financing conditions. We examine R&D expenditure, R&D personnel, R&D intensity, the ratio and amount of intangible assets, capitalized R&D, and financing constraints. The financing-constraint measure is the absolute value of the SA index following Hadlock and Pierce (2010); under the present coding, lower values indicate weaker financing constraints. For heterogeneity analysis, firm and industry characteristics are fixed using information observed before persistence confirmation. Treated firms use the last nonmissing value before the confirmation year, whereas never-treated firms use the first nonmissing observed value. Continuous moderators, including digital foundation, R&D foundation, and HHI, are divided at the median of the resulting firm-level distribution; high-technology and competitive-industry indicators retain their binary values. Because the first qualifying year of the two-year ownership spell can precede confirmation by one year, these moderators are referred to throughout as pre-confirmation rather than strictly pre-exposure characteristics. Digital Foundation and R&D Foundation are continuous measures contained in the CSMAR dataset; Table 1 reports the operational definitions used in the empirical analysis.

Table 1. Variable Definitions

Variable	Code	Definition / Measurement	Role
Persistent State Entry (≥5%)	persistent_state_entry	Aggregate state ownership ≥5% in two adjacent calendar years; equals 1 from the second qualifying year (persistence-confirmation year) onward and remains 1 thereafter	Treatment
AI Breadth	ai_breadth	Number of distinct AI-related keywords with WordFrequency > 0 in the CSMAR MD&A text for a firm-year	Outcome
AI Patents	ai_patent	ln[1 + (RInvig + RInvjg)], using CSMAR group-level granted AI invention patents	Outcome
Firm Size	size	Natural logarithm of total assets	C1

Variable	Code	Definition / Measurement	Role
Leverage	lev	Total liabilities / total assets	C1
ROA	roa	CSMAR return-on-assets measure	C1
Growth	growth	Year-on-year growth in operating revenue	C1
Cash Flow	cashflow	Net operating cash flow / total assets	C1
Tobin's Q	tobinq	CSMAR Tobin's Q market-valuation measure	C2
Asset Turnover	ato	Operating revenue / average total assets	C2
Fixed-Asset Intensity	fixed	Net fixed assets / total assets	C2
Loss	loss	1 if the firm reports a loss in the year, 0 otherwise	C2
Listing Age	listage	ln(1 + years since initial public offering)	C2
Board Size	board	Natural logarithm of the number of directors	C3
Independent Directors	indep	Independent directors / total directors	C3
CEO-Chair Duality	dual	1 if the board chair also serves as CEO/general manager, 0 otherwise	C3
Largest Shareholder Ownership	top1	Ownership share of the largest shareholder	C3
Big Four Auditor	big4	1 if the auditor is a Big Four accounting firm, 0 otherwise	C3
Industry Concentration	hhi	CSMAR Herfindahl-Hirschman Index (HHI) of industry concentration; larger values indicate greater concentration	C3 / Heterogeneity
R&D Expenditure	rd_spend	Logarithmic measure of annual R&D expenditure	Mechanism
R&D Personnel	rd_staff	Logarithmic measure of the number of R&D personnel	Mechanism
R&D Intensity	rd_intensity	R&D expenditure / total assets	Mechanism
Intangible Asset Ratio	intangible_ratio	Intangible assets / total assets	Mechanism

Variable	Code	Definition / Measurement	Role
Intangible Asset Amount	intangible_amount	Signed logarithmic measure of the absolute amount of intangible assets	Mechanism
Capitalized R&D	cap_rd	Logarithmic measure of capitalized R&D expenditure	Breadth mechanism
Financing Constraints	sa_abs	Absolute value of the SA financing-constraint index; lower values indicate weaker constraints in the present coding	Patent mechanism
Digital Foundation	digital_foundation	CSMAR-based continuous measure; heterogeneity uses the latest available value before persistence confirmation for treated firms and the first observed value for never-treated firms, split at the firm-level median	Heterogeneity
R&D Foundation	rd_foundation	CSMAR-based continuous measure; heterogeneity uses the latest available value before persistence confirmation for treated firms and the first observed value for never-treated firms, split at the firm-level median	Heterogeneity
High-Tech Industry	hightech_industry	High-technology-industry status measured before persistence confirmation; treated firms use the latest pre-confirmation value and never-treated firms use the first observed value	Heterogeneity
Competitive Industry	competitive_industry	Competitive-industry status measured before persistence confirmation; treated firms use the latest pre-confirmation value and never-treated firms use the first observed value	Heterogeneity

Notes: C1, C2, and C3 are predetermined nested control sets; mechanism and heterogeneity variables are excluded from the baseline control vector. All variables are obtained from or constructed from CSMAR data. For heterogeneity analysis, treated firms use the latest available value before persistence confirmation and never-treated firms use the first available value; continuous moderators are split at the firm-level median. Because the first qualifying ownership year may occur before confirmation, these characteristics are described as pre-confirmation rather than strictly pre-exposure measures.

3.3 Empirical Specifications

3.3.1 Baseline Specification

Equation (1) estimates the within-firm relationship between persistence-confirmed state participation and the two AI outcomes. Firm fixed effects absorb time-invariant firm characteristics. Industry-by-year fixed effects absorb annual industry-specific technology, demand, and regulatory shocks, while province-by-year fixed effects absorb contemporaneous regional policy, financial, infrastructure, and macroeconomic conditions. Standard errors are clustered at the firm level. Because treatment timing is nonrandom and staggered across firms, the coefficient is interpreted as a conditional within-firm estimate rather than as a design-based causal effect. Conventional two-way fixed-effects estimates can also be sensitive to heterogeneous treatment effects under staggered adoption (Baker et al., 2022; Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021; Imai & Kim, 2021; Sun & Abraham, 2021). We

therefore interpret the baseline estimates together with event-time diagnostics, falsification tests, and sensitivity analyses.

$$Y_{it} = \beta\ \mathrm{PersistentStateEntry}_{it} + \gamma' \mathrm{Controls}_{it} + \mu_i + \lambda_j \times_t + \theta_p \times_t + \varepsilon_{it} \quad (1)$$

In Equation (1), the dependent variable is either AI Breadth or AI Patents, and the control vector follows the C1, C2, or C3 specification. All nested-control columns are estimated on the same final C3 sample. Holding the sample fixed makes coefficient changes across C1-C3 directly comparable and prevents missing-data differences from being mistaken for robustness to additional controls.

3.3.2 Event-Study and Dynamic Effects

The event study sets the persistence-confirmation year - the second consecutive year with aggregate state ownership of at least 5% - to event time zero and uses t = -1 as the omitted reference period. Event times t <= -4 and t >= 4 are grouped into distant pre- and post-confirmation bins, respectively, while the remaining years are estimated separately. Because t = -1 can be the first qualifying year with state ownership already at or above 5%, it is a pre-confirmation reference period rather than a guaranteed zero-exposure year. The event-time coefficients therefore describe dynamics around confirmation of persistence, not necessarily around first state-capital exposure. The specification retains C3 controls, firm, industry-by-year, and province-by-year fixed effects, with standard errors clustered by firm.

$$Y_{it} = \Sigma_{k \neq -1}\ \beta_k\ 1(\mathrm{EventTime}_{it}=k) + \gamma' \mathrm{Controls}_{it} + \mu_i + \lambda_j \times_t + \theta_p \times_t + \varepsilon_{it} \quad (2)$$

The pre-period diagnostic jointly tests whether the coefficients for t <= -4, t = -3, and t = -2 equal zero relative to the omitted t = -1 period. Failure to reject this null is interpreted as an absence of a detectable differential pattern in these earlier event-time coefficients, not as proof of untreated parallel trends. This distinction matters because the reference year can already contain the first qualifying 5% holding and because pre-trend tests may have limited power (Roth, 2022). For presentation, Figure 1 re-normalizes the same estimated coefficients relative to the mean of the three earlier pre-periods; the underlying regression and the formal joint test are unchanged. Interpretation remains subject to the general limitations of conventional event studies under staggered adoption and treatment-effect heterogeneity (Borusyak et al., 2024; Callaway & Sant'Anna, 2021; Rambachan & Roth, 2023; Sun & Abraham, 2021).

3.3.3 Mechanism Tests

For each mediator-outcome pair, the mechanism analysis uses a common complete-case sample and estimates three linked regressions: the association between state participation and the outcome, the association between state participation and the proposed mediator, and an outcome regression containing both state participation and the mediator. Indirect effects for the common mechanisms are summarized with a parametric distribution-of-product Monte Carlo procedure, while capitalized R&D and financing constraints use Sobel/Delta inference. These exercises are designed to assess whether the data are consistent with the proposed channels. They are not treated as a separately identified causal mediation design, which would require stronger assumptions about mediator-outcome confounding and temporal ordering (Imai et al., 2010).

$$M_{it} = a\ \mathrm{Treat}_{it} + \gamma' \mathrm{Controls}_{it} + \mathrm{FE} + u_{it}; \quad Y_{it} = c'\ \mathrm{Treat}_{it} + b\ M_{it} + \gamma' \mathrm{Controls}_{it} + \mathrm{FE} + \varepsilon_{it} \quad (3)$$

3.3.4 Heterogeneity Specification

The heterogeneity regressions interact Persistent State Entry with firm or industry characteristics fixed before persistence confirmation. Treated firms use the last available pre-confirmation observation, while never-treated firms use the first available observation. Continuous moderators are split at the firm-level median and binary industry indicators retain their observed values. Because the first qualifying ownership year may precede confirmation, these characteristics are interpreted as pre-confirmation conditions rather than strictly pre-exposure traits. The resulting grouping variables are time-invariant within firms, so their main effects are absorbed by firm fixed effects and the interaction coefficient directly tests whether the conditional association differs across groups. The same C3 controls and fixed-effects structure are retained.

$$Y_{it} = \beta_1 \, Treat_{it} + \beta_2 (Treat_{it} \times H_i) + \gamma' Controls_{it} + \mu_i + \lambda_j \times_t + \theta_p \times_t + \varepsilon_{it} \quad (4)$$

3.4 Descriptive Statistics, Correlations, and Multicollinearity Diagnostics

In the 18,657-observation common sample, AI Breadth averages 1.726 (median 1), AI Patents 0.097 (median 0), and Persistent State Entry 0.035. Descriptive statistics, correlations, and VIF diagnostics are reported in Supplementary Tables S1–S3; the VIF results indicate no severe multicollinearity among included regressors.

4. Empirical Results

4.1 Baseline Results

Table 2 reports the baseline estimates. The coefficients on Persistent State Entry for AI Breadth are 0.274, 0.277, and 0.268 across C1, C2, and C3, respectively, and remain positive with statistical support around the 10% level. The corresponding AI Patent coefficients are 0.061, 0.059, and 0.059 and are significant at the 5% level. In the full C3 specification, persistence-confirmed state participation is associated with 0.268 additional distinct AI-related terms in MD&A and a 0.059 increase in the log patent measure. The patent result is particularly useful because it shows that the estimated relationship is not confined to annual-report language. Overall, the nested specifications indicate a stable positive conditional association, with stronger statistical evidence for patent output.

Table 2. Baseline and Nested-Control Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
	Breadth: C1	**Patent: C1**	**Breadth: C2**	**Patent: C2**	**Breadth: C3**	**Patent: C3**
Persistent State Entry >=5%	0.274*	0.061**	0.277*	0.059**	0.268*	0.059**
	(1.862)	(2.171)	(1.877)	(2.115)	(1.812)	(2.108)
Firm Size	0.452***	0.045***	0.453***	0.046***	0.444***	0.047***
	(8.402)	(5.186)	(7.490)	(4.725)	(7.148)	(4.858)
Leverage	-0.561***	-0.036	-0.645***	-0.030	-0.640***	-0.030
	(-3.169)	(-1.289)	(-3.664)	(-1.058)	(-3.594)	(-1.067)
ROA	0.065	-0.047	0.068	-0.062	0.073	-0.062
	(0.244)	(-0.984)	(0.259)	(-1.266)	(0.277)	(-1.266)
Growth	-0.054	-0.015**	-0.070*	-0.016**	-0.070*	-0.016**
	(-1.459)	(-2.342)	(-1.760)	(-2.329)	(-1.742)	(-2.349)
Cash Flow	-0.063	0.057	-0.165	0.054	-0.165	0.055
	(-0.279)	(1.451)	(-0.731)	(1.390)	(-0.728)	(1.405)
Tobin Q			0.009	-0.002	0.009	-0.002
			(0.515)	(-0.770)	(0.521)	(-0.766)
Asset Turnover			0.138	0.019	0.134	0.019
			(1.255)	(1.125)	(1.221)	(1.163)
Fixed-Asset Intensity			0.014	0.023	0.020	0.022
			(0.056)	(0.646)	(0.080)	(0.623)
Loss			0.019	-0.008	0.018	-0.008
			(0.403)	(-0.923)	(0.370)	(-0.915)
Listing Age			0.198*	-0.030*	0.201*	-0.030*
			(1.904)	(-1.799)	(1.913)	(-1.790)
Board Size					0.159	-0.022
					(0.656)	(-0.550)
Independent Directors					0.172	-0.091
					(0.253)	(-0.762)
CEO-Chair Duality					0.026	0.002
					(0.562)	(0.264)
Largest Shareholder Ownership					-0.100	-0.004
					(-0.299)	(-0.075)
Big Four Auditor					0.109	-0.024
					(0.589)	(-0.863)
Industry Concentration					0.273	0.017
					(0.611)	(0.251)
Constant	-7.939***	-0.867***	-8.357***	-0.859***	-8.563***	-0.802***
	(-6.860)	(-4.702)	(-6.601)	(-4.162)	(-6.165)	(-3.314)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes

	(1)	(2)	(3)	(4)	(5)	(6)
	Breadth: C1	**Patent: C1**	**Breadth: C2**	**Patent: C2**	**Breadth: C3**	**Patent: C3**
Province x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm
Observations	18657	18657	18657	18657	18657	18657
F-statistic	13.397	6.153	9.072	3.776	6.205	2.562

Notes: All columns use the same final C3 estimation sample after singleton removal. Continuous variables are winsorized at the 1st and 99th percentiles. Firm, industry×year, and province×year fixed effects are included. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels.

4.2 Event-Time Dynamics

Table 3 reports event-time estimates around the persistence-confirmation year. For AI Breadth, the coefficients at t <= -4, t = -3, and t = -2 are -0.253, -0.273, and -0.110; the corresponding AI Patent coefficients are -0.049, -0.022, and -0.014. None is individually statistically significant, and the joint p-values are 0.395 for AI Breadth and 0.508 for AI Patents. Thus, the data do not reveal a detectable joint differential pattern in these earlier periods relative to t = -1. Because t = -1 may already contain the first qualifying 5% state holding, this result is interpreted as a pre-confirmation diagnostic rather than a conventional untreated parallel-trends test.

The post-confirmation dynamics differ across the two outcomes. AI Breadth is positive in the confirmation year and the following year and remains positive at later horizons, but the estimates become imprecise and the joint post-period p-value is 0.677. AI Patents display a clearer delayed pattern: the joint post-period p-value is 0.033, and the coefficient for t >= 4 is 0.156 and significant at the 5% level. This delayed patent pattern is consistent with the time required for technical development, filing, examination, and authorization, although grant timing can also reflect inventions initiated before confirmation. Figure 1 presents the same event-time estimates graphically.

Table 3. Event-Time Estimates and Pre-Period Diagnostics

	(1)	(2)
	AI Breadth	**AI Patents**
ev_pre4	-0.253	-0.049
	(-1.235)	(-1.476)
ev_pre3	-0.273	-0.022
	(-1.635)	(-0.724)
ev_pre2	-0.110	-0.014
	(-0.923)	(-0.536)
ev0	0.115	0.006
	(0.992)	(0.222)
ev_post1	0.239	0.010
	(1.439)	(0.267)
ev_post2	0.025	-0.017
	(0.125)	(-0.463)
ev_post3	0.068	-0.012
	(0.311)	(-0.271)
Observations	18657	18657
F-statistic	4.624	2.226
Joint Pre-trend p-value	0.40	0.51
Joint Post-treatment p-value	0.677	0.033

Notes: t=-1 is the omitted reference period. Because persistent participation is confirmed in the second consecutive year with state ownership >=5%, t=-1 may already contain the first qualifying 5% holding and is therefore a pre-confirmation rather than guaranteed zero-exposure reference year. The formal joint pre-period test covers t<=-4, t=-3, and t=-2. All specifications include C3 controls, firm FE, industry x year FE, province x year FE, and firm-clustered standard errors.

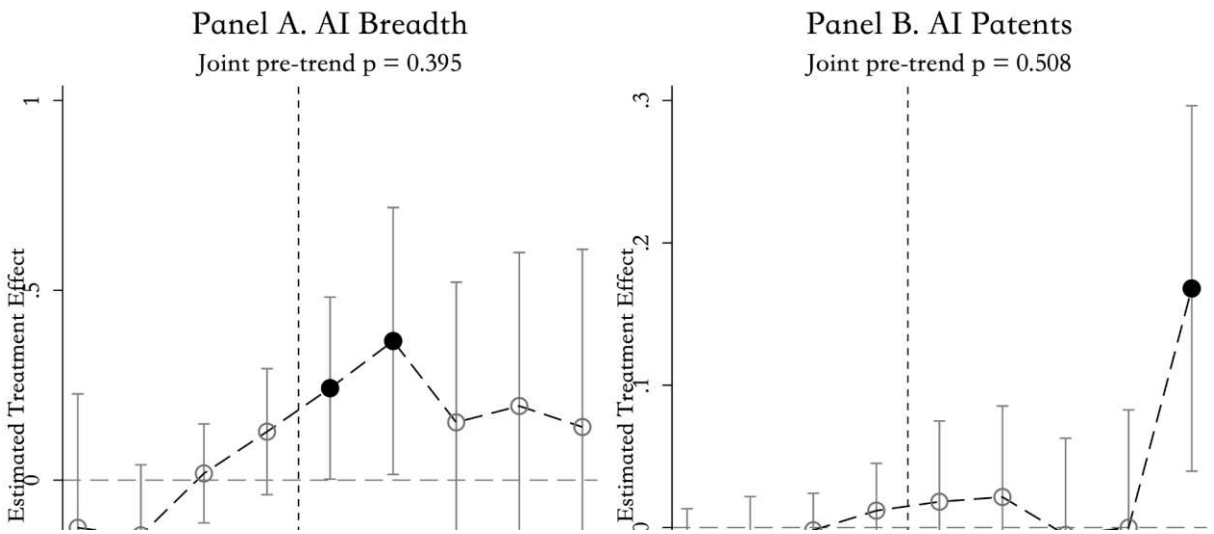


Figure 1. Event-Time Estimates around Persistence Confirmation

Notes: 95% confidence intervals are reported. Filled markers denote p<0.10 under the average-pre graphical normalization. The formal pre-period tests are those reported in Table 3 with t=-1 omitted. The figure describes dynamics around persistence confirmation and should not be interpreted as evidence of a fully untreated pre-period.

4.3 Robustness Tests

4.3.1 Two-Way Clustered Inference

Table S4 reports two-way clustered standard errors by firm and calendar year. Because only the variance estimator changes, the point estimates remain 0.268 for AI Breadth and 0.059 for AI Patents, and both retain statistical support at the 10% level. The result indicates that the positive coefficients are not specific to firm-only clustering, although inference with a limited number of year clusters remains less precise.

4.3.2 Sample-Period Sensitivity

Table S5 varies the sample period. Moving the start year to 2012, 2013, and 2014 yields AI Breadth coefficients of 0.271, 0.280, and 0.282 and AI Patent coefficients of 0.056, 0.057, and 0.054. Ending the sample in 2023 produces coefficients of 0.248 and 0.046, while restricting the period to 2013-2023 yields 0.268 and 0.045. The point estimates remain positive in every window. The breadth estimates generally retain marginal statistical support, while the patent estimates remain statistically supported at the 5% or 10% level depending on the sample window. The stability of signs and magnitudes across windows supports the baseline pattern.

4.3.3 Required Pre/Post Observation Support

Table S6 requires treated firms to have sufficient observations on both sides of the persistence-confirmation year. Across the four support rules, the AI Breadth coefficient ranges from 0.269 to 0.283 and the AI Patent coefficient from 0.060 to 0.071. The patent estimates remain significant at the 5% level in all four specifications, while the breadth estimates remain positive and close to the 10% threshold. The results reduce concern that the baseline estimates are driven by treated firms observed only briefly around the confirmation event.

4.3.4 Excluding Early Treatment Cohorts

Table S7 excludes firms whose persistence-confirmation year falls in 2011-2015. After removing these early cohorts, the AI Breadth coefficient increases from 0.268 to 0.308 and is significant at the 5% level, while the AI Patents coefficient is 0.065 and is also significant at the 5% level. The restricted sample contains 18,530 firm-year observations. The baseline pattern is therefore not driven exclusively by the earliest confirmation cohorts.

4.4 Endogeneity Diagnostics and Falsification Tests

4.4.1 Controls Lagged Two Periods

Contemporaneous firm characteristics may respond to state participation or AI activity, creating a risk of conditioning on covariates that move simultaneously with the event. Table S8 therefore replaces the C3 controls with values lagged by two periods. Lagged variables are generated on the full panel before sample restrictions are imposed, and missing lags created by gaps in the panel are not imputed. The requirement for longer firm histories reduces the estimation sample to 12,905 observations. This exercise reduces, but does not eliminate, concerns about post-event adjustment in contemporaneous controls.

With controls lagged two years, the coefficients remain positive at 0.284 for AI Breadth and 0.056 for AI Patents, and both receive statistical support at the 10% level. The breadth coefficient is slightly larger than the baseline estimate, while the patent coefficient remains close to 0.059. The result indicates that moving the controls farther back in time does not materially alter the baseline association.

4.4.2 Fake-Timing Placebo Tests

The fake-timing tests construct pseudo-treatment windows beginning two, three, or four years before the actual persistence-confirmation year and ending immediately before confirmation. The regressions use only observations before actual confirmation together with never-treated observations. For AI Breadth, the pseudo-treatment coefficients are 0.207, 0.125, and 0.071; for AI Patents, they are 0.026, 0.029, and 0.034. None reaches conventional significance levels. The exercise therefore does not reveal a systematic pre-confirmation pattern at deliberately incorrect earlier timings. Because these windows extend through t=-1, which can already contain the first qualifying state holding, the test is best viewed as a falsification around the confirmation date rather than as a placebo based entirely on zero-exposure observations.

4.4.3 Year-Stratified Randomization Placebo

Table S10 and Figure 2 summarize a year-stratified randomization placebo. In the reported 100-replication implementation, the actual estimates of 0.268 for AI Breadth and 0.059 for AI Patents lie in the tails of the simulated coefficient distributions, producing plus-one empirical p-values of 0.010. With 100 replications, however, 0.010 is approximately the minimum attainable empirical p-value under the plus-one correction, and the permutation scheme does not preserve complete firm-level absorbing treatment paths. We therefore use this exercise as an auxiliary sensitivity diagnostic rather than as stand-alone randomization inference.

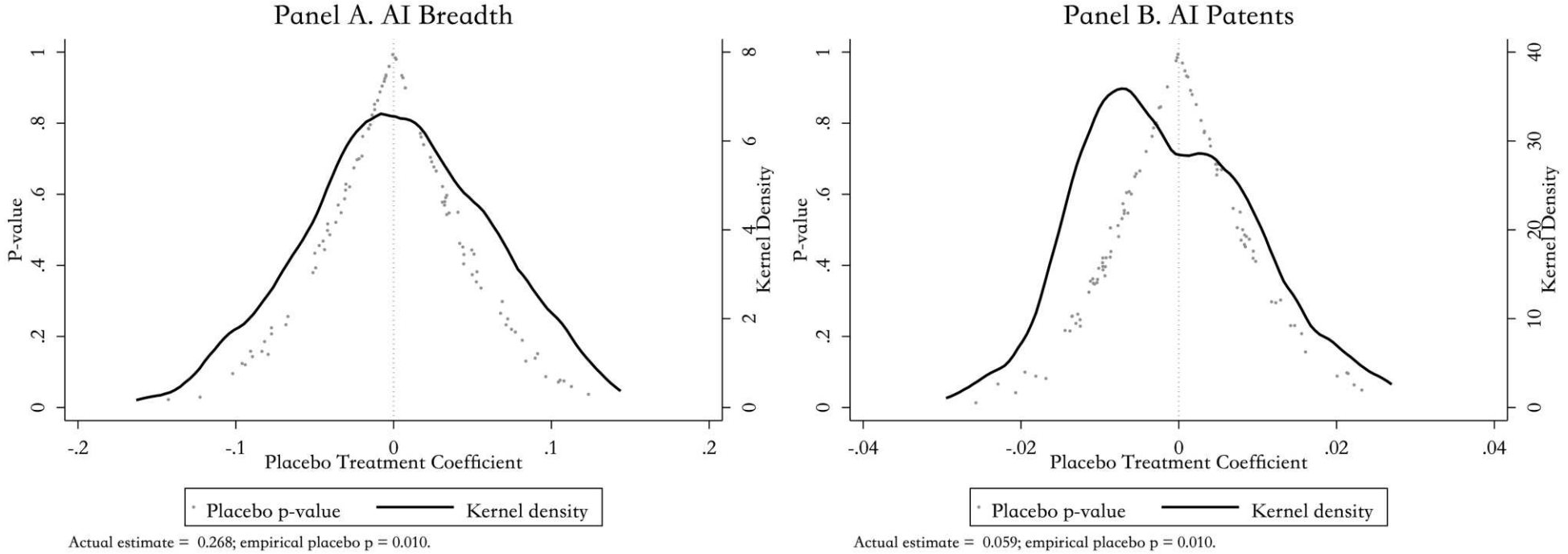


Figure 2. Year-Stratified Randomization Placebo Tests

Notes: Dots report placebo p-values and solid lines report kernel densities of placebo treatment coefficients. Actual estimates and empirical placebo p-values are printed below each panel. The exercise uses 100 within-year label permutations and is interpreted as a sensitivity diagnostic rather than a separate identification strategy.

4.4.4 Future-Treatment Falsification

The future-entry falsification asks whether firms that will reach persistence confirmation one, two, or three years later already display systematically different current AI outcomes. The estimated AI Breadth coefficients are 0.202, 0.096, and -0.114, with t-statistics of 1.375, 0.798, and -0.794; the corresponding AI Patent coefficients are 0.027, 0.011, and 0.006, and none is statistically significant. The two- and three-year leads provide the cleaner pre-confirmation diagnostics. The one-year lead should be interpreted more cautiously because it can coincide with the first qualifying year of the two-year ownership spell. Overall, the estimates do not reveal a systematic pattern well in advance of persistence confirmation, although they do not rule out selection on unobserved or slowly evolving characteristics.

4.4.5 Oster-Style Coefficient-Stability Diagnostic

The omitted-variable sensitivity exercise follows Oster (2019) and compares the Persistent State Entry coefficient and within R-squared between a restricted model and the full C3 specification. With Rmax set to 1.3 times the full-model within R-squared, the implied delta is 7.298 for AI Breadth and 12.907 for AI Patents. Under the stated proportional-selection assumptions and calibration, these values imply that selection on unobservables would need to be relatively strong, compared with selection on observables, to move the estimated coefficients to zero. Because the within R-squared values are small and the calculation is calibration-dependent, the result is treated as a sensitivity diagnostic rather than as evidence that omitted-variable bias has been eliminated.

4.5 Mechanism-Consistency Evidence

4.5.1 R&D Resources and Intangible-Asset Accumulation

Table S13 examines R&D resources and knowledge-asset accumulation. Persistent State Entry is positively associated with R&D expenditure, and R&D expenditure is positively associated with both AI outcomes. The implied indirect-effect estimates are 0.0183 for AI Breadth and 0.0014 for AI Patents, with Monte Carlo p-values of 0.059 and 0.074. The evidence is therefore suggestive rather than definitive, but it is directionally consistent with a resource-expansion channel.

The R&D personnel results are more precise. Persistent state participation is positively associated with the size of the R&D workforce, and R&D personnel are positively associated with both AI outcomes. The estimated indirect effect is 0.0212 for AI Breadth with a Monte Carlo p-value of 0.033 and 0.0014 for AI Patents with a p-value of 0.074. R&D intensity points in the same direction. Taken together, the expenditure, personnel, and intensity results are consistent with H2's emphasis on technical-resource accumulation, while remaining descriptive mechanism evidence rather than a causal decomposition of the total coefficient.

4.5.2 Outcome-Specific Mechanisms

The outcome-specific tests distinguish channels related to the scope of AI engagement from those tied to downstream patent output. For AI Breadth, Capitalized R&D has an a-path coefficient of 1.123 with a p-value of 0.055, and the implied indirect effect is 0.0236 with a Sobel p-value of 0.091. The total Persistent State Entry coefficient in this mediator-specific sample is 0.467, and the direct coefficient remains 0.443 after Capitalized R&D is included. The pattern is consistent with part of the breadth association operating through the capitalization of R&D into longer-lived technical assets, although the indirect-effect evidence is marginal.

The financing-constraint evidence is stronger for AI Patents. Persistent State Entry is associated with a 0.021 reduction in the absolute SA index ($p = 0.002$), which under the present coding indicates weaker financing constraints. The SA measure is negatively associated with AI Patents, producing a positive indirect-effect estimate of 0.0073 with a Sobel p-value of 0.022. The direct coefficient remains positive at 0.052 after the SA measure is included. These results are consistent with H3 and with the view that sustained financing conditions are particularly relevant for downstream technological output, while remaining mechanism-consistency evidence rather than identified causal mediation.

4.6 Heterogeneity Analysis

The heterogeneity analysis interacts Persistent State Entry with firm or industry characteristics measured before persistence confirmation. The interaction coefficient, rather than a comparison of separate subgroup p-values, is used to assess whether the conditional association differs across capability or market conditions. Because the first qualifying ownership year may occur before confirmation, the moderators are interpreted as pre-confirmation characteristics rather than strictly pre-exposure attributes.

4.6.1 Pre-Confirmation Digital Foundation

Digital foundation generates the largest cross-group difference. In the low-digital-foundation group, the Persistent State Entry coefficients are -0.603 for AI Breadth and -0.075 for AI Patents. The interactions with High Pre-confirmation Digital Foundation are 1.227 and 0.189, respectively, and both are significant at the 1% level. The estimates therefore indicate a pronounced difference between firms with weaker and stronger digital foundations, rather than a uniform positive relationship. Because Table 4 does not report the standard error of the high-group linear combination, we do not infer the significance of the high-group marginal coefficient by mechanically adding the main and interaction terms. The significant interaction nevertheless identifies digital capability observed before persistence confirmation as an important boundary condition, consistent with H4.

4.6.2 Pre-Confirmation R&D Foundation and High-Technology Status

R&D foundation shows a similar complementarity. The interaction coefficients are 0.517 for AI Breadth and 0.115 for AI Patents and are significant at the 5% level, while the main Persistent State Entry coefficient for the low-R&D-foundation group is not statistically significant. High-technology-industry status points in the same direction: the interaction coefficient is 0.701 for AI Breadth and significant at the 5% level, while the AI Patent interaction is 0.093 and significant at the 10% level. Together, these specifications are consistent with an absorptive-capacity interpretation in which state-linked resources have greater technological value when stronger technical capabilities are already observable before persistence is confirmed.

4.6.3 Industry Competition

Competition is examined using two measures with opposite scaling but consistent economic content. The interaction with the Pre-confirmation Competitive Industry indicator is 0.510 for AI Breadth and 0.124 for AI Patents; the former is significant at the 10% level and the latter at the 5% level. Using HHI, the Persistent State Entry coefficients in the low-HHI group are 0.760 for breadth and 0.108 for patents, while the interactions with High Pre-confirmation HHI are -0.933 and -0.092. The negative HHI interactions indicate that the conditional relationship weakens as industry concentration rises. For AI Breadth, the point estimates imply substantial attenuation in the high-HHI group, although Table 4 does not report the uncertainty of the relevant linear combination and no significance claim is made for that marginal effect. The agreement between the competition indicator and HHI reduces dependence on a single market-structure classification.

Table 4. Heterogeneity by Pre-Confirmation Firm and Industry Characteristics

Panel / Variable	*AI Breadth*	*AI Patents*
Panel A. High Pre-confirmation Digital Foundation		
Persistent State Entry (≥5%)	-0.603***	-0.075***
	(-5.203)	(-5.176)
State Entry x High Pre-confirmation Digital Foundation	1.227***	0.189***
	(5.820)	(4.831)
Observations	18,327	18,327
Panel B. High Pre-confirmation R&D Foundation		
Persistent State Entry (≥5%)	-0.126	-0.029
	(-0.770)	(-0.912)
State Entry x High Pre-confirmation R&D Foundation	0.517**	0.115**
	(2.184)	(2.515)
Observations	18,646	18,646
Panel C. Pre-confirmation High-Tech Industry		
Persistent State Entry (≥5%)	-0.198	-0.003
	(-0.979)	(-0.081)

Panel / Variable	*AI Breadth*	*AI Patents*
State Entry × High-Tech Industry	0.701**	0.093*
	(2.567)	(1.840)
Observations	18,657	18,657
Panel D. Pre-confirmation Competitive Industry		
Persistent State Entry (≥5%)	-0.163	-0.046
	(-0.671)	(-1.085)
State Entry × Competitive Industry	0.510*	0.124**
	(1.761)	(2.337)
Observations	18,657	18,657
Panel E. High Pre-confirmation HHI		
Persistent State Entry (≥5%)	0.760***	0.108**
	(3.077)	(2.422)
State Entry x High Pre-confirmation HHI	-0.933***	-0.092*
	(-3.350)	(-1.666)
Observations	18,657	18,657
Controls	C3	C3
Firm FE	Yes	Yes
Industry × Year FE	Yes	Yes
Province × Year FE	Yes	Yes
Clustered SE	Firm	Firm

Notes: The coefficient of interest is the interaction between Persistent State Entry and the pre-confirmation grouping variable. Treated firms use the last nonmissing value before persistence confirmation and never-treated firms use the first nonmissing observed value; continuous moderators are split at the firm-level median. Because the first qualifying ownership year may precede confirmation, these characteristics are not interpreted as strictly pre-exposure measures. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

4.7 Summary of Empirical Evidence

Overall, persistence-confirmed state participation is positively associated with both outcomes, with stronger patent evidence. Sensitivity and falsification checks generally support the sign of the baseline estimates but do not eliminate selection concerns. Mechanism tests are consistent with technical-resource and financing channels, not causally identified mediation. Digital and R&D foundations and competitive pressure strongly condition the associations.

5. Discussion

5.1 Interpreting Minority State Ownership as a Conditional Resource Arrangement

The results concern a hybrid arrangement in which private control persists alongside minority state ownership. Positive average estimates fit a resource-based interpretation, while substantial heterogeneity shows that access to state-linked resources alone is insufficient. The findings identify conditional complementarities, not a general causal effect of ownership change.

5.2 Measurement Implications for Corporate AI Research

AI Breadth and AI Patents reflect different stages. Breadth tends to respond earlier but less precisely, while patent associations are more evident after longer lags. Disclosure thus should not be equated with technological implementation, and grant timing should not be read as the invention date. Using both outcomes provides a more nuanced account than either alone.

5.3 Practical Implications

Policy and managerial implications are conditional. Minority state shareholding may complement existing digital infrastructure, R&D capacity, and competitive incentives; it cannot substitute for them. Firms should evaluate the governance demands and technical readiness accompanying any state-linked investment. The present estimates do not establish that arranging such investment would itself raise AI activity.

6. Conclusion

6.1 Main Findings

Using 2010–2025 CSMAR data on privately controlled listed firms, we examine AI disclosure breadth and granted invention patents after minority state ownership has remained at least 5% for two consecutive years. The full models show positive associations (0.268 for breadth; 0.059 for patents), with stronger patent evidence. Patent outcomes show clearer longer-horizon differences, while R&D, staffing, intangible assets, and financing measures provide mechanism-consistency evidence. Technological foundations and industry competition shape the estimates.

The findings support a conditional resource-and-governance account of minority state ownership: access to additional resources appears most consequential where firms already have the capability and incentive to transform them into AI output.

6.2 Limitations and Future Research

Several limitations constrain interpretation. First, ownership persistence is nonrandom; fixed effects, event studies, and falsification checks do not establish causality. Second, the event is persistence confirmation rather than initial exposure, and $t = -1$ may already contain a qualifying stake. Third, heterogeneous effects under staggered timing may complicate conventional fixed-effects estimates, notwithstanding sensitivity tests. Fourth, sample selection and changing patterns of disclosure or patent examination can affect generalizability.

AI Breadth measures disclosure rather than implementation, while granted patents omit nonpatented applications and lag inventive activity. The contemporaneous mechanism regressions are associative, not causally identified mediation. Future research could combine AI employment, recruitment, software investment, and patent text with stronger identification of initial state-capital exposure.

Data Availability

The study uses licensed China Stock Market & Accounting Research (CSMAR) data. Access to the underlying proprietary records is subject to CSMAR licensing restrictions. The authors should provide the editors and reviewers with the shareable cleaned analytical data, variable construction documentation, and analysis code through the submission system or an approved repository, subject to their data-use agreement. Repository links and the precise list of materials made available must be inserted and verified before resubmission.

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