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Digital Economy Policy Exposure and Firms' Innovation in Key Core Technologies

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Abstract. Digital policy can influence strategic innovation through policy exposure, complementary organizational investment, and lengthy technology-conversion cycles. This study examines whether intelligent manufacturing policy is associated with firms' innovation in key core technologies among Chinese listed companies. Policy exposure is defined by whether an industry was prioritized by the policy and whether the observation falls in the post-policy period. A difference-in-differences framework with firm and year fixed effects is used to estimate relative changes in patent outcomes. The results show a positive post-policy association for granted key core technology patents, including alternative outcome measures based on transformed grants and patent citations. The financing-constraint result does not support a financing-relief mechanism, whereas the decline in industry concentration is consistent with a more competitive market structure. The technical-personnel share does not change significantly. Estimated associations are stronger among firms with greater digital-technology use and higher robot penetration. However, the event-study evidence does not adequately support parallel trends. The findings should therefore be interpreted as conditional associations rather than definitive causal effects.

Keywords: Digital economy policy exposure, Intelligent manufacturing, Key core technology innovation, Difference-in-differences, Patent grants

1. Introduction

Key core technologies support long-term competitive advantage, industrial-chain resilience, and high-quality development. Compared with incremental improvement, these technologies require longer development cycles, greater investment, and higher tolerance for failure. Firms therefore need sustained R&D capacity, stable financing, and skilled personnel. Cloud computing, big data, artificial intelligence, and the industrial internet are changing knowledge acquisition, resource allocation, and R&D organization. Whether digital policy produces strategic patents within a short window remains an empirical question.

Digital innovation research shows that digital technologies reshape innovation actors, boundaries, and organizational processes [1-5]. Productivity gains also depend on organizational capital, management practices, and complementary intangible investment. These gains may follow a pronounced productivity J-curve [6, 7]. Broadband complements skilled labour, indicating that

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infrastructure does not automatically generate innovation performance [8]. Evidence from Chinese digital patents also links digital technology innovation to high-quality firm development [9]. Direct evidence on long-cycle strategic technologies nevertheless remains limited.

Industrial-policy research emphasizes targeting, implementation capacity, and firm responses [10]. Chinese studies examine key core technology breakthroughs through key laboratories, ESG practices, and manufacturing innovation measures [11-13]. Research on patent value and resource allocation also shows that simple counts do not fully measure innovation quality [14]. This study asks whether priority industries changed relatively after 2015 and whether financing, workforce, or market structure changed alongside patents. It distinguishes policy exposure from actual firm digitalization and reports the identification limits together with the estimates.

2. Literature review and theoretical analysis

2.1. Digital innovation, industrial policy, and key core technologies

Digital technologies can reduce knowledge-search, information-transmission, and cross-organizational coordination costs. They may also improve the visibility and dynamic allocation of R&D projects. Intelligent manufacturing policy can change innovation conditions through demonstration, resource guidance, and standard setting. However, strategic technologies have long development cycles, and digital returns require organizational and skill complements. Short-run patent changes may therefore understate longer-run effects. This reasoning motivates the directional hypothesis below.

H1: Exposure of policy-priority industries to intelligent manufacturing policy is positively associated with firms' innovation in key core technologies.

2.2. Mechanisms and hypotheses

First, digital operations and disclosure may reduce information asymmetry and improve financial assessment of firms and R&D projects. Long and uncertain innovation projects require financing arrangements that match experimentation [15]. If this channel operates, policy exposure should move the financing-constraint measure toward weaker constraints.

Second, key core technology innovation requires R&D personnel, technical staff, and highly educated employees. Information technology often complements skilled labour and organizational redesign [7, 8]. Policy exposure may therefore increase demand for technical personnel and improve workforce allocation.

H2a: Policy exposure reduces firms' financing constraints. H2b: Policy exposure increases the share of technical personnel.

Third, digital technologies improve access to market information and responses to competitive change. Firms may seek differentiation through strategic innovation. Industrial policy can also alter entry, resource allocation, and concentration [10]. A lower industry HHI indicates a less concentrated market, but it does not alone establish a complete competitive mechanism.

H2c: Exposure of policy-priority industries is associated with lower industry concentration.

2.3. Heterogeneity

Ownership affects access to policy resources, financing, and innovation incentives. Technological and asset intensity shape resource allocation. Digital use, internet business models, manufacturing

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digitalization, information systems, and robot penetration reflect firms' capacity to absorb policy. The analysis uses direct between-group coefficient tests rather than comparing significance across separate regressions.

3. Research design

3.1. Policy background, data, and sample construction

The State Council issued Made in China 2025 in 2015 under State Council Document No. 28 [16]. The policy emphasized integrating information technology with manufacturing and identified intelligent manufacturing as a central direction. Existing code classifies industries C26-C29 and C34-C39 as policy-priority industries. Their interaction with years from 2015 onward defines did. This classification is researcher-constructed exposure, not an official list of pilot firms. Accordingly, the treatment group denotes policy-priority industries rather than policy-covered firms.

The key core technology patent data are matched to the Industrial Foundation Innovation Catalogue and originally cover 2007-2024. The regression package covers A-share listed firms from 2012 to 2022. Financial firms and firms with ST or PT status during the sample are excluded. The sample retains Shanghai and Shenzhen A-share firms, and continuous controls are winsorized annually at 1%. The final sample contains 2,677 firms and 23,161 firm-year observations. PPData states that the patent database is intended for academic research.

3.2. Variable definitions

Table 1 summarizes the variables used in the analysis.

Table 1. Variable definitions

Variable category	Variable	Definition
Outcome	patent1	Number of granted key core technology patents
Logged outcome	ln(1+patent1)	Natural logarithm of one plus granted key core technology patents
Alternative outcome	patent3	Data-package measure of citations to granted key core technology patents
Policy exposure	did	Priority-industry status interacted with the post-2015 period
Controls	ROA1/Intangible/TobinQ/ListAge/Top1	Profitability, intangible assets, growth, listing age, and ownership concentration
Financing constraints	SA	Raw negative SA index; more negative values usually indicate tighter constraints

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Table 1. (continued)

Workforce composition	S	Technical personnel as a percentage of employees
Market structure	HHI_A	Sum of squared industry revenue shares; higher values indicate greater concentration
Ownership and industry	SOE/technology intensity/asset intensity	Firm and industry indicators used for heterogeneity
Digital absorption	Digital measures/robot penetration	High and low groups split at cleaned-sample medians

Note: The data label for patent1 is the number of granted core patents. The manuscript therefore uses patent grants rather than patent applications. Patent3 is labelled as citations to granted core patents. Its exact transformation should be verified against the data dictionary. The raw SA index is negative, and more negative values usually indicate tighter financing constraints.

3.3. Model specification

The study uses the following two-way fixed-effects DID-style specification in equation (1):

$$Y_{it} = \beta\, DID_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

In equation (1), Y_{it} denotes firm i's innovation in year t. DID_{it} interacts priority-industry status with the post-2015 period. X_{it} contains firm-level controls, while μ_i and λ_t denote firm and year fixed effects. Treatment status uses each firm's annual industry code, and 117 firms switch between priority and control industries. The specification is therefore not a strict fixed-group, common-adoption DID. Treatment should be fixed using pre-policy industry codes, or switchers should be modelled separately. Current tables cluster standard errors by firm, although treatment varies mainly at the industry-year level. Industry-level or two-way clustering should be checked. The coefficient β measures a relative change, not the effect of actual digital use.

4. Empirical results

4.1. Descriptive statistics

Table 2 reports descriptive statistics for the analysis sample.

Table 2. Descriptive statistics

Variable	N	Mean	Std. dev.	Min.	Max.
ln(1 + granted key core technology patents)	23,161	0.223	0.615	0.000	6.852
Granted key core technology patents	23,161	1.357	17.088	0.000	945.000
Any granted key core technology patent	23,161	0.169	0.375	0.000	1.000
DID	23,161	0.344	0.475	0.000	1.000
ROA	22,027	0.043	0.063	-0.662	1.285
Intangible asset ratio	23,086	0.049	0.064	0.000	0.852

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Table 2. (continued)

Tobin's Q	22,655	1.891	1.342	0.625	31.400
Listing age	22,975	2.213	0.887	0.000	3.497
Largest-shareholder ownership	23,160	35.991	15.383	0.286	89.986
Technical personnel share	22,239	19.676	16.542	0.060	96.600
SA financing-constraint index	23,151	-3.849	0.276	-5.690	-2.094
Industry HHI	20,821	0.141	0.150	0.000	1.000

Note: The full sample matches the policy panel to the key core technology patent data. Patent outcomes are right-skewed and contain many zeros. The analysis therefore reports raw grants, logged grants, and an alternative measure.

4.2. Baseline results

Table 3 reports the baseline estimates across the three patent outcomes.

Table 3. Baseline results

Model	DID coefficient	Std. error	p-value	N	Adjusted R^2
Patent grants, no controls	1.149*	(0.662)	0.083	23,161	0.009
Patent grants, with controls	1.323*	(0.726)	0.069	21,643	0.010
ln(1 + patent grants)	0.083***	(0.019)	0.000	21,643	0.048
Granted-patent citation measure (patent3)	0.439***	(0.048)	0.000	21,643	0.379

Note: All models include firm and year fixed effects. Current standard errors are clustered by firm. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 3 reports a DID coefficient of 1.323 for raw patent grants after controls, with $p = 0.069$. The logged-grant coefficient is 0.083, with $p < 0.001$. The patent3 citation coefficient is 0.439, with $p < 0.001$. All three estimates are positive, but the raw-count result is significant only at 10%. The magnitude and precision therefore depend on outcome construction. Because pre-policy event-study coefficients are significant, these estimates indicate association rather than a fully identified causal effect.

4.3. Mechanism tests

Table 4 reports the mechanism-test estimates.

Table 4. Mechanism tests

Mechanism outcome	DID coefficient	Std. error	p-value	N	Adjusted R^2
Technical personnel share (S)	0.571	(0.422)	0.176	20,809	0.019
SA financing-constraint index	-0.017***	(0.004)	0.000	21,633	0.839
Industry concentration (HHI)	-0.025***	(0.004)	0.000	19,373	0.292

Note: These regressions relate policy exposure to intermediate outcomes. One intermediate-outcome regression cannot establish a complete mediation chain. Current standard errors are clustered by firm.

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Table 4 reports 0.5708 for the technical-personnel share, with p = 0.176. The estimate is not statistically significant. The SA coefficient is −0.0166, with p < 0.001. Because raw SA values are negative, a more negative index usually indicates tighter financing constraints. The result therefore does not support H2a unless the variable was recoded in the source data. The HHI coefficient is −0.0248, with p < 0.001, which is consistent with lower concentration. This association alone does not establish competition as a mediator of patent outcomes. H2b is unsupported, H2a has the opposite direction, and H2c receives only intermediate-outcome support.

4.4. Heterogeneity

Table 5 reports heterogeneity by ownership, technology intensity, and asset intensity.

Table 5. Heterogeneity by ownership, technology intensity, and asset intensity

Subgroup or difference	DID coefficient	Std. error	p-value	N
Non-state-owned firms	0.050**	(0.024)	0.039	12,627
State-owned firms	0.144***	(0.034)	0.000	9,016
Non-technology-intensive industries	0.046*	(0.025)	0.068	13,029
Technology-intensive industries	0.056	(0.040)	0.163	8,614
Non-asset-intensive firms	0.100***	(0.022)	0.000	17,490
Asset-intensive firms	0.011	(0.041)	0.784	4,153
Ownership difference	0.070*	(0.036)	0.053	21,643
Technology-intensity difference	0.049	(0.032)	0.125	21,643
Asset-intensity difference	-0.054	(0.035)	0.122	21,643

Note: Between-group differences equal the high-group DID coefficient minus the low-group coefficient. Models include firm and year fixed effects and the baseline controls.

Table 6 reports heterogeneity by firms' digital absorption and robot penetration.

Table 6. Heterogeneity by digital absorption

Subgroup or difference	DID coefficient	Std. error	p-value	N
Low digital-technology use	0.034	(0.021)	0.105	8,493
High digital-technology use	0.122***	(0.036)	0.001	13,114
Low internet business model	0.038	(0.024)	0.114	9,349
High internet business model	0.123***	(0.030)	0.000	12,258
Low manufacturing digitalization	0.026	(0.016)	0.120	10,517
High manufacturing digitalization	0.082**	(0.040)	0.041	11,090
Low modern information systems	0.069***	(0.023)	0.003	10,236
High modern information systems	0.070**	(0.032)	0.031	11,371
Low robot penetration	0.063***	(0.022)	0.004	10,685
High robot penetration	0.107***	(0.027)	0.000	10,709

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Table 6. (continued)

Digital-technology-use difference	0.048***	(0.018)	0.009	21,607
Internet-business-model difference	0.012	(0.019)	0.508	21,607
Manufacturing-digitalization difference	0.036*	(0.019)	0.062	21,607
Modern-information-system difference	0.009	(0.018)	0.634	21,607
Robot-penetration difference	0.028**	(0.012)	0.021	21,394

Note: Digitalization and robot variables are split at the cleaned-sample median. Missing values are excluded from the corresponding subgroup regressions. Interpretation relies on direct between-group tests.

Tables 5 and 6 show an ownership difference with p = 0.053. Differences by digital-technology use and robot penetration are significant at 1% and 5%, respectively. The manufacturing-digitalization difference is near the 10% level. Differences by technological intensity, asset intensity, internet business model, and modern information systems are not conventionally significant. These patterns are exploratory because the current design does not adequately support parallel trends.

4.5. Event study, parallel trends, and robustness

Table 7 reports the event-study estimates used to assess parallel trends and robustness.

Table 7. Event-study estimates and parallel-trends assessment

Relative policy year	Coefficient	Std. error	p-value
pre_3	-0.944	(0.741)	0.203
pre_2	-1.224*	(0.631)	0.053
pre_1	-1.008**	(0.498)	0.043
current	-0.384	(0.261)	0.141
las_1	-0.275	(0.230)	0.231
las_2	0.086	(0.256)	0.735
las_3	0.273	(0.302)	0.365
las_4	0.557	(0.346)	0.107
las_5	0.716*	(0.391)	0.067
las_6	1.136*	(0.583)	0.051
las_7	1.559**	(0.684)	0.023

Note: Pre-policy periods are pre_3 to pre_1, the policy year is current, and post-policy periods are las_1 to las_7. The output does not identify the normalized omitted period. This must be checked against the code and software output.

Pre_2 and pre_1 are significant at the 10% and 5% levels. The current results therefore do not adequately support equal pre-policy trends. Las_5 and las_6 are near the 10% level, while las_7 is significant at 5%. These dynamics cannot be interpreted causally without resolving the pre-trend problem. Logged patent grants and patent3 remain positively significant, showing robustness to some outcome definitions but not to identification failure.

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Figure 1 reports event-study coefficients and 95% confidence intervals. Figure 2 reports annual raw means of ln(1 + granted key core technology patents). Together, the figures show pre-existing level and trend differences between treatment and control industries.

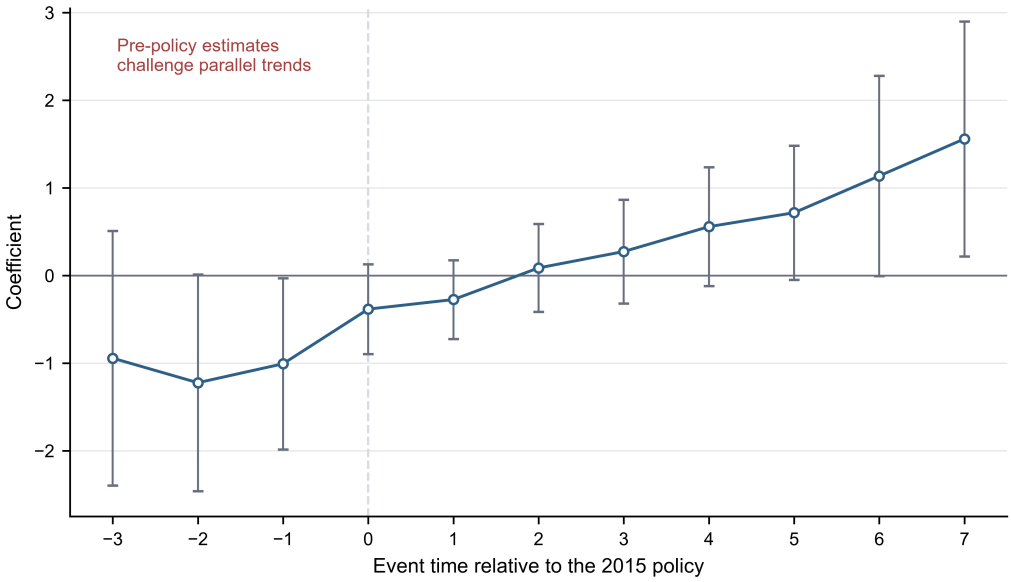


Figure 1. Dynamic estimates and parallel-trends assessment

Note: Error bars show 95% confidence intervals. Pre_2 and pre_1 are significant at 10% and 5%, respectively. The normalized omitted period is not identified in the current output.

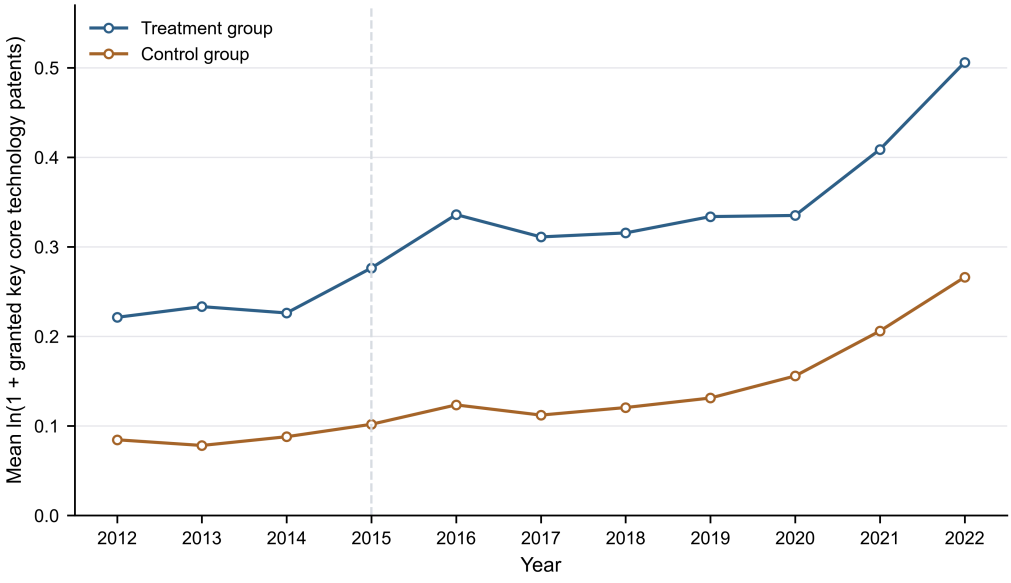


Figure 2. Trends in granted key core technology patents by treatment status

Note: The dashed line marks 2015. Values are unadjusted annual means in the cleaned sample, not covariate-adjusted causal estimates.

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5. Further discussion

The baseline estimates are positive across patent measures, but the identification limits preclude a definitive policy-causal interpretation. General-purpose technologies often require organizational capital and complementary intangible investment, with long adjustment periods [5, 6]. Strategic technologies also require time to progress from R&D to grants and citations. However, treatment industries followed different pre-2015 trajectories. Industry selection, concurrent policies, or initial innovation capacity may therefore explain part of the post-policy difference.

The study has five main limitations. First, annual industry-code exposure is not an official pilot list, and 117 firms switch groups. Second, the event study does not adequately support parallel trends, and its normalization period needs verification. Third, the clustering level may not match industry-level treatment. Fourth, supply-chain spillovers, regional policy, and concurrent industrial policies may contaminate comparisons. Fifth, the transformation of patent3 and the direction of SA require confirmation. Future work should fix treatment using pre-policy codes or model switchers, use official pilots, improve inference, and examine longer-run patent quality.

6. Conclusions and policy implications

Using Chinese A-share firms from 2012 to 2022, this study examines relative changes in priority industries after the 2015 policy. DID coefficients are positive for raw grants, logged grants, and the granted-patent citation measure. Significant pre-policy coefficients nevertheless weaken causal interpretation. Mechanism regressions do not support financing relief or a higher technical-personnel share. Lower HHI provides only intermediate evidence consistent with reduced concentration. The most defensible conclusion is that priority industries show a stronger post-2015 patent association, but the design cannot attribute it entirely to policy.

Policy evaluation should not equate digital investment with short-run patent counts. Governments can support long-horizon R&D and patient capital, connect digital infrastructure to industrial innovation platforms, and strengthen technical training and collaboration. Evaluation should also consider grant quality, citations, and long-run value. These recommendations follow from the long development cycle of strategic technologies, not from treating the current regressions as fully identified effects.

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