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Science and Technology Finance and the Development of New Quality Productive Forces in the Artificial Intelligence Industry

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Abstract. The artificial intelligence (AI) industry is a strategic emerging sector with strong innovation potential but high financing pressure. In the Chinese policy context, developing new quality productive forces (NQPF) requires financing structures that support technological upgrading, long investment cycles, and high uncertainty. Using firm-level panel results from the original draft, this paper examines how four financing channels—government subsidies, technology credit, internal financing, and equity financing—are associated with NQPF in AI firms from 2020 to 2025. The panel includes 3,906 firm-year observations for 651 firms. A fixed-effects model is used as the baseline specification, with a standardized random-effects model as a robustness check. The baseline results show that government subsidies and equity financing are positively associated with NQPF, while debt financing and internal financing have no significant effects during the sample period. Firm size and net profit margin are negatively associated with the dependent variable in the reported specification. The findings suggest a structural mismatch in the current science and technology finance system: financing channels suited to long-horizon innovation appear more effective, whereas conventional credit and retained internal funds provide weaker support. The paper argues that policy should promote a coordinated financing system based on targeted public support, patient equity capital, and innovation-oriented credit instruments.

Keywords: Artificial Intelligence Industry, New Quality Productive Forces, Science and Technology Finance, Financing Structure, Fixed Effects Model

1. Introduction

The concept of new quality productive forces (NQPF) has become an important policy framework for explaining high-quality development in China. Official English-language explanations define NQPF as advanced productivity led by innovation and characterized by high technology, high efficiency, and high quality [1]. This framework is especially relevant to the artificial intelligence (AI) industry, since AI integrates algorithmic innovation, data, software, computing infrastructure, and industrial application, thereby reshaping production processes and business models. OECD research similarly regards AI as a general-purpose technology whose productivity effects depend on

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complementary intangible and tangible inputs, including software, data, skills, and computing capacity [2]. AI is therefore both a strategic emerging industry and an important carrier of NQPF.

Recent evidence shows that financing is increasingly crucial for AI-led upgrading. The 2025 AI Index reports that global private investment in generative AI reached US$33.9 billion in 2024, while 78% of organizations used AI, a sharp increase from the previous year [3]. UNCTAD also finds that AI development, R&D resources, and computing infrastructure are highly concentrated among a small number of firms and countries [4]. Thus, AI firms' ability to compete depends heavily on sustained financing for model development, data acquisition, computing power, talent, and commercialization.

Studies on AI and productivity further suggest that financing must support not only invention but also diffusion and organizational transformation. AI adoption is usually gradual and requires complementary investment, especially in intangible assets that are difficult to finance [2]. Firm-level evidence shows that generative AI can improve productivity, particularly for less experienced workers, but broader gains depend on organizational learning and adjustment [5, 6].

This financing challenge is especially important because intangible-intensive investment is hard to value, collateralize, and appropriate [7]. Evidence from Europe shows that high-intangible firms are more productive and more likely to become market leaders, yet also face stronger financial constraints [8]. Long-horizon equity mechanisms such as venture capital are therefore important for uncertain, high-growth innovation [9], whereas close bank–firm relationships may discourage exploratory innovation [10]. Liquidity and institutional investors can also support intangible investment and equity financing [11, 12]

For China, policy-supported financing matters for strategic emerging industries. Zhang, Luo, and Xiang [13] show that related policies improve firm innovation partly through tax benefits, loans, and R&D input. However, little is known about which financing channels best foster NQPF in AI firms. This paper addresses that gap by examining government subsidies, debt finance, internal finance, and equity finance in Chinese AI firms from 2020 to 2025.

2. Financing needs in the development of new quality productive forces in the AI industry

The first reason why AI firms have strong financing needs is the long and uncertain path from research input to productive output. Innovation in AI often requires repeated experiments, model adjustment, computing infrastructure, data acquisition, and talent recruitment before commercial returns become visible. This means that the financial cycle is usually longer than the production cycle, and the value of the investment may only appear after several rounds of iteration. Studies on innovation finance have repeatedly shown that such conditions create a funding gap because outside investors cannot easily judge the quality or timing of future returns [14]. In the context of NQPF, this problem becomes even more important because firms are not only producing new technologies but also trying to transform the quality and efficiency of production itself.

The second reason is the asset structure of AI firms. Many AI enterprises are asset-light in the traditional accounting sense because their core resources are data, software, models, patents, and human capital rather than buildings or equipment. These assets are valuable, but they are difficult to collateralize in standard bank lending. As a result, conventional debt finance often becomes less suitable, especially in early and middle stages of development. The broader literature on innovative firms shows that access to finance is harder when firms depend heavily on intangible investment and cannot present easily verifiable collateral to lenders [15]. This helps explain why credit channels may remain active in nominal terms while still contributing little to real innovation upgrading.

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The third reason is that AI competition requires speed as well as scale. In many subfields, late entry can quickly weaken a firm's position because model performance, user data, ecosystem access, and platform effects all reward early movers. This creates demand for finance that is not only patient but also scalable. Research on high-tech firms shows that new equity financing often plays a stronger role than debt in supporting growth when firms face capital market imperfections and limited borrowing capacity [16]. For AI firms, this logic is particularly strong because expansion often requires front-loaded spending on infrastructure, application scenarios, and talent, while revenue may remain unstable for a long period.

The fourth reason is that financing needs change across development stages. Early-stage firms may benefit more from subsidies and venture-style equity because the uncertainty is highest and private credit is hardest to obtain. As firms mature, they may gradually gain access to more diversified funding sources, but even then innovation projects can remain exposed to financing constraints. Evidence from R&D-intensive firms suggests that internal finance and external finance affect innovation differently depending on firm age, growth stage, and the characteristics of investment opportunities [17]. Therefore, a science and technology finance system that aims to support NQPF should not rely on a single instrument. It should match channels to technological stage, risk profile, and governance needs.

3. Research design and empirical results

3.1. Data and variable design

This study uses the firm-level panel dataset reported in the Wind Database and the Guotai Junan Database. The sample covers the period from 2020 to 2025 and contains 3,906 firm-year observations from 651 firms, which indicates a balanced six-year panel. The empirical work was implemented in Stata, and the panel structure is defined at the firm level. Table 1 summarizes the types, codes, meanings, and measurement methods of the main variable.

The dependent variable is NQPF, which measures the firm-level development of new quality productive forces in AI firms. This study uses the "enterprise new quality productivity level" indicator provided in the CSMAR database rather than constructing a new index independently. In this dataset, NQPF is a composite indicator constructed from two main dimensions: labor and production tools. The labor dimension is calculated from living labor and materialized labor. Living labor reflects the quality of human capital and is based on standardized indicators such as the share of R&D personnel salaries, the proportion of R&D employees, and the proportion of highly educated employees. Materialized labor reflects the input of production objects and is calculated from standardized indicators such as the fixed-asset ratio and manufacturing expense ratio. The production-tool dimension is calculated from hard technology and soft technology. Hard technology captures firms' technological input and asset base, including standardized measures such as R&D depreciation and amortization, R&D leasing expenses, direct R&D input, and intangible assets. Soft technology reflects operational and organizational efficiency and is measured by standardized indicators such as total asset turnover and the reciprocal of the equity multiplier. The final NQPF value is obtained through the weighted aggregation of the labor and production-tool dimensions. A higher value indicates a higher level of firm-level new quality productive forces. This definition is consistent with the variable design in the original database and helps ensure that the empirical specification is aligned with the official data source.

The four core explanatory variables represent different financing channels. Government subsidies (gov) measure public support intensity, debt financing (deb) captures the scale of science and technology credit, internal financing (intf) reflects internally accumulated funds, and equity financing (equf) measures support from capital markets. Following the design in the draft, these variables are constructed mainly in logarithmic form. The control variables are firm size (Size), development potential (dev), firm age (year1), and net profit margin (NPM). Size is measured by the logarithm of total assets, dev by the logarithm of R&D investment, year1 by years since establishment, and NPM by net profit divided by operating revenue.

The table 2 descriptive statistics show substantial heterogeneity across firms. The mean of NQPF is 0.0046, with a standard deviation of 0.0082 and a maximum value of 0.1508, suggesting that firm-level productivity upgrading differs widely within the AI industry. Government subsidies, debt financing, internal financing, and equity financing also display wide dispersion, which supports the use of panel regression rather than a simpler cross-sectional comparison. Net profit margin is especially volatile, ranging from -6.1675 to 3.5769, which indicates that the sample includes firms at very different stages of profitability and adjustment.

Table 1. Variable design

Variable type	Code	Variable	Meaning	Measurement
Dependent variable	NQPF	New quality productive forces in AI	Innovation and efficiency upgrading	Composite firm-level index in the original dataset
Explanatory variable	gov	Government subsidy	Intensity of government support	Log of subsidy amount
Explanatory variable	deb	Technology credit	Support from credit system	Log of short-term and long-term credit
Explanatory variable	intf	Internal financing	Support from internal funds	Log of capital reserve plus retained earnings
Explanatory variable	equf	Equity financing	Support from capital market	Log of total equity financing
Control variable	Size	Firm size	Scale level	Log of total assets
Control variable	dev	Development potential	Growth and innovation capacity	Log of R&D investment
Control variable	year1	Firm age	Life-cycle stage	Years since establishment
Control variable	NPM	Net profit margin	Profitability	Net profit / operating revenue

Table 2. Descriptive statistics

Variable	Obs.	Mean	Std. dev.	Min	Max
NQPF	3906	0.0045958	0.0081897	0.0001797	0.150788
gov	3906	16.36496	1.996089	0	22.42
deb	3906	17.30727	6.656521	0	25.6724
intf	3906	19.36194	2.20159	0	25.69
equf	3906	22.81948	1.011058	20.11	27.9
Size	3906	22.37025	1.222551	19.5205	27.2348
dev	3906	18.77957	1.482689	0	24.0576
year1	3906	25.0169	6.302346	9	67
NPM	3906	0.0106051	0.2893488	-6.167512	3.576868

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3.2. Model specification

To examine the association between financing structure and NQPF, the paper adopts a firm-level fixed-effects model as the baseline specification:

$$NOPF\_it = \alpha + \beta_1 gov\_it + \beta_2 deb\_it + \beta_3 intf\_it$$

$$+\beta_4 equf\_it + \gamma X\_it + \mu\_i + \varepsilon\_it$$

where i denotes firm, t denotes year, X_it is the vector of control variables, μ_i captures unobserved firm-specific effects, and ε_it is the idiosyncratic error term. The use of firm fixed effects is appropriate because AI firms differ in many stable but hard-to-observe characteristics, such as founder quality, technological route, governance structure, market niche, and data endowment. If these firm-specific traits are correlated with financing choices, pooled estimation may bias the coefficients. The reported F test that all firm effects equal zero strongly rejects the pooled alternative, which supports the panel treatment in the baseline results.

3.3. Baseline fixed-effects results

Table 3 reports the main fixed-effects estimation. Two results stand out. First, government subsidies show a positive coefficient of 0.0001202 and are significant at the 10 per cent level. This suggests that public support is positively associated with productivity upgrading in the AI industry. The result is consistent with the argument that targeted subsidies can relax financing constraints, signal project quality, and make firms more willing to sustain risky innovation investment [18]. In the AI context, subsidies may be especially useful where firms face long horizons, uncertain returns, and weak collateral.

Second, equity financing shows a positive coefficient of 0.0004472 and is also significant at roughly the 10 per cent level. Among the four financing channels, this is the largest positive coefficient in the reported fixed-effects model. The result supports the view that equity-type capital is better matched to the financing logic of AI firms because it can bear uncertainty, tolerate long payback periods, and support scaling before cash flow becomes stable [19]. This is also broadly in line with the literature showing that innovative and high-growth firms often rely on new equity financing when debt markets are less supportive [16].

By contrast, debt financing does not show a significant effect. Its coefficient is very small and statistically insignificant. This suggests that, during the sample period, technology credit did not translate into observable upgrading in firm-level NQPF. A likely explanation is that the formal label of "technology credit" does not by itself solve the underlying information and collateral problems that innovative firms face. Bank lending can remain cautious even under policy encouragement when projects are difficult to value and downside risk is high, which is a common pattern in studies of financing barriers for innovative firms [20]. In practical terms, the result implies that credit finance in the AI industry may still be more available than effective.

Internal financing is also insignificant in the baseline model. The coefficient is close to zero and does not support a strong positive role for retained internal funds during the observed period. This result is interesting because classic theory often suggests that firms prefer internal resources when outside finance is costly or information-sensitive [21]. However, the AI sector may provide a different short-run picture. Internal funds can be limited in young or fast-growing firms, and profitable firms may still find that retained earnings are too small or too unstable to meet large investment needs in data, computing, and talent. In addition, managerial preferences may push

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internal cash toward risk control or short-term balance sheet repair rather than aggressive innovation spending, which echoes the broader agency-based concern that internal cash is not always used in the most productive way [22].

Firm size enters with a negative and significant coefficient, while net profit margin is also negative and significant. A negative size effect does not mean that large firms are generally unproductive. In the present specification, it suggests that, after controlling for firm fixed effects and the reported financing variables, larger asset scale is associated with lower measured NQPF. One possible interpretation is that some larger AI-related firms carry legacy assets, organizational inertia, or expansion burdens that slow the conversion of financing into productivity upgrading. The negative coefficient on net profit margin may reflect a tension between short-term profitability and long-term innovation expenditure, especially when firms are still in a heavy investment stage. Since the baseline output omits dev and year1, the control structure should not be over-interpreted beyond what is directly reported.

Table 3. Fixed-effects results

Variable	Coef.	Std. Err.	t	P>|t|	95% confidence interval
gov	0.0001202	0.0000655	1.84	0.066	-0.0000082 to 0.0002486
deb	0.00000543	0.0000251	0.22	0.829	-0.0000437 to 0.0000546
intf	0.00000569	0.0001242	0.05	0.963	-0.0002379 to 0.0002493
equf	0.0004472	0.0002296	1.95	0.052	-0.0000030 to 0.0008974
Size	-0.0013040	0.0003749	-3.48	0.001	-0.0020391 to -0.0005690
dev	omitted	—	—	—	—
year1	omitted	—	—	—	—
NPM	-0.0014470	0.0003502	-4.13	0.000	-0.0021335 to -0.0007604
Constant	0.0214069	0.0087224	2.45	0.014	0.0043049 to 0.0385089

F test that all u_i = 0: F(650, 3249) = 15.78; Prob > F = 0.0000

3.4. Robustness and endogeneity discussion

The table 4 reported random-effects results, government subsidies remain positive and become significant at the 5 per cent level, while equity financing is again positive and statistically significant. Debt financing and internal financing remain insignificant. Firm size is still significantly negative, development potential becomes significantly positive, firm age remains insignificant, and net profit margin remains significantly negative.

The supplementary random-effects model helps with robustness, but it does not eliminate the possibility of reverse causality or omitted time-varying factors. For example, firms with better latent technological potential may be more likely to attract both subsidies and equity financing. Similarly, investors may select firms that are already on a stronger productivity-upgrading path. A strict endogeneity strategy would require additional tools such as instrumental variables, lagged financing measures, or dynamic panel estimators. Because the available results do not report such tests, the present paper does not claim full causal identification. Instead, it makes the more defensible statement that the observed financing channels are systematically associated with differences in NQPF.

Table 4. Supplementary standardized random-effects results

Variable	Coef.	Std. Err.	z	P>|z|	95% confidence interval
gov_std	0.0301811	0.0151451	1.99	0.046	0.0004973 to 0.0598649
deb_std	0.0018491	0.0197846	0.09	0.926	-0.0369280 to 0.0406261
intf_std	-0.0173957	0.0311628	-0.56	0.577	-0.0784737 to 0.0436822
equf_std	0.0667558	0.0253026	2.64	0.008	0.0171635 to 0.1163481
size_std	-0.1627223	0.0415380	-3.92	0.000	-0.2441354 to -0.0813093
dev_std	0.0726732	0.0248927	2.92	0.004	0.0238845 to 0.1214619
year1_std	0.0063149	0.0347610	0.18	0.856	-0.0618154 to 0.0744452
NPM_std	-0.0474622	0.0120097	-3.95	0.000	-0.0710007 to -0.0239237
Constant	1.05e-09	0.0340937	0.00	1.000	-0.0668224 to 0.0668224

Random-effects GLS regression, Number of obs = 3,906; Number of groups = 651; Wald chi2(8) = 40.41; Prob > chi2 = 0.0000; rho = 0.71253371

4. Problems in science and technology finance for AI-led NQPF

The empirical results point to several structural problems in the current science and technology finance system for the AI industry. The first problem is an imbalance across financing channels. The channels that show stronger positive links with NQPF are government subsidies and equity financing, while debt and internal funds do not show meaningful effects in the baseline model. This means that the financing structure is not neutral. Some channels appear much better aligned with the needs of AI-led productivity upgrading than others. If most financing support continues to rely on instruments that are not well matched to the innovation cycle, then the overall financial system may look active while its real allocation efficiency remains limited.

The second problem is that credit finance has not yet adapted well to the economic logic of AI innovation. The insignificant debt coefficient suggests that technology credit still faces weak transmission to firm-level productivity upgrading. This is consistent with the long-standing view that innovative firms face credit rationing when lenders cannot easily evaluate project quality or recover value from intangible assets [23]. In the AI industry, these problems are even sharper because key assets often take the form of data resources, models, software systems, and specialized teams. If lending standards remain tied mainly to fixed assets, short-term profits, or conventional collateral, then credit programs labeled as "technology finance" may still fail to serve the firms they are meant to support.

The third problem is the limited effectiveness of internal accumulation in a sector that requires patient and scalable capital. In theory, internal finance can reduce information costs and allow firms to avoid external control pressure. In practice, the present results suggest that internal funds did not play a strong role in NQPF upgrading during the sample period. One reason may be that many AI firms simply do not generate enough retained earnings to support frontier innovation at scale. Another reason may be that internal funds are used defensively, especially under uncertainty, rather than being directed toward risky but transformative investment. The broader innovation literature shows that the relationship between internal finance and R&D is real but uneven, and it can vary strongly with firm size, age, and financing constraints [24]. In a capital-hungry sector like AI, internal funds alone may be too narrow a base.

The fourth problem concerns the allocation efficiency of public support. The positive government subsidy coefficient is encouraging, but it should not be read as proof that all subsidy spending is efficient. Public support can work well when it relaxes real bottlenecks and mobilizes further investment, but it can work poorly when it is fragmented, overly administrative, or disconnected from firm capability. Earlier research suggests that public R&D support can stimulate business R&D, but the effect depends on design, targeting, and the interaction between public and private incentives [25]. In the AI industry, this means that the key issue is not only whether subsidies exist, but whether they reach firms and projects that can convert funding into real productivity gains.

The fifth problem is unequal access to effective equity finance. The positive coefficient on equity financing suggests that equity-based support is valuable, but access to such capital is not evenly distributed. Firms with stronger networks, better locations, more visible founders, or easier exit prospects are more likely to attract patient capital. This can create a dual structure inside the AI industry, where a small group of firms gains repeated access to high-quality financing while many others remain outside the most effective channels. If this pattern persists, the sector may experience concentration without broad-based productivity upgrading. From a policy perspective, this is not only a firm-level problem but also a system-level challenge in how science and technology finance selects, evaluates, and scales emerging firms.

5. Policy recommendations

First, to address the imbalance across financing channels, policy should establish a stage-matched financing structure for AI-led NQPF. The empirical results show that government subsidies and equity financing are positively associated with NQPF, while debt financing and internal financing are not significant in the observed sample. This means that the policy objective should not be a general expansion of technology finance, but a better matching of instruments to firms' innovation stages and risk profiles. Subsidies should mainly support early exploration, public-good research, and shared technological infrastructure; equity financing should support risk-bearing, scaling, and commercialization under uncertainty; and credit should become more important only when firms have clearer innovation outputs, contracts, cash-flow visibility, or collateralizable intangible assets. Such a layered structure directly responds to the problem of channel imbalance and can improve the allocation efficiency of science and technology finance.

Second, to solve the weak transmission of technology credit, innovation-oriented credit should be redesigned around intangible assets and risk-sharing mechanisms. The insignificant debt coefficient suggests that traditional lending standards remain poorly connected to the economic logic of AI innovation. Banks should therefore move beyond fixed-asset collateral and short-term profitability indicators, and give greater weight to intellectual property, data resources, model capability, computing infrastructure, application contracts, and R&D continuity. In practice, this requires stronger intellectual property pledge systems, data-asset valuation rules, cash-flow-based lending, credit products for computing infrastructure and model deployment, and government-backed guarantee or risk-compensation arrangements. Consistent with the broader view that financial development supports innovation through institutional design rather than credit expansion alone [19], credit policy should focus on valuation reform, information disclosure, and risk sharing so that loans can support real productivity upgrading rather than only increasing the nominal scale of credit.

Third, to overcome the limited role of internal accumulation and the unequal access to effective equity finance, policy should expand patient capital while widening the pipeline of firms that can reach it. AI firms often require long-horizon capital that can tolerate delayed returns, absorb technological failure, and provide governance support. Venture capital, private equity, corporate

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venture capital, and long-horizon industrial funds are therefore better suited than retained earnings alone for many high-uncertainty AI projects. This is consistent with evidence that venture-backed finance is closely related to stronger innovation outcomes in high-growth sectors [26]. However, equity finance should not remain concentrated only in a few core cities, well-known platforms, or elite firms. Policy should improve regional fund-of-funds systems, encourage cross-regional syndication, support public-private co-investment, and strengthen exit channels and market transparency. These measures would reduce the dual structure in which only highly visible firms obtain patient capital, while other technologically capable firms remain trapped in weak financing environments.

Fourth, to improve the allocation efficiency of public support, subsidy policy should become more targeted, catalytic, and performance-oriented. The positive subsidy coefficient shows that public support matters, but it does not imply that all subsidies are equally effective. Subsidies should be used where market finance is least willing to enter but social spillovers are high, such as basic research, common technology platforms, testing and evaluation infrastructure, high-end talent formation, data governance systems, and early-stage engineering transformation. They should also be designed to crowd in follow-up private investment rather than replace market selection. Competitive grants, milestone-based support, matching funds, and ex post evaluation can help reduce fragmented or purely administrative allocation. Evidence from grant-based innovation policy shows that public funding can attract later private investment when it reduces early information and financing frictions [18]. For AI firms, this means that subsidy rules should distinguish exploratory research, engineering transformation, commercial deployment, and ecosystem-building tasks instead of applying one common standard to all firms.

Fifth, to deal with firm heterogeneity and the limits of purely financial screening, science and technology finance should be linked to capability-based assessment and longer evaluation horizons. The strong firm effects in the panel results indicate that financing effectiveness depends not only on the amount and channel of funding, but also on technological capability, organizational learning, computing resources, data governance, and application scenarios. Policy can therefore support specialized science and technology finance platforms that combine financial review with expert technological assessment. These platforms could evaluate patents and models, technical teams, computing-power plans, industrial application scenarios, and governance capacity before recommending subsidies, equity participation, or credit support. At the same time, evaluation should not rely only on short-term numerical targets such as the number of funded projects or one-year revenue growth. A more suitable framework should include medium- and long-term indicators such as innovation quality, productivity upgrading, platform effects, diffusion capacity, and spillover potential. This would align policy assessment with the concept of NQPF, which emphasizes qualitative improvement rather than simple scale expansion.

6. Conclusion

This paper reworks the original draft into a full English academic manuscript and examines how science and technology finance is associated with the development of new quality productive forces in the AI industry. Using a balanced panel of 651 firms and 3,906 firm-year observations from 2020 to 2025, the study compares four financing channels within a fixed-effects framework. The main result is that government subsidies and equity financing are positively associated with firm-level NQPF, while debt financing and internal financing do not show significant effects in the reported baseline. A supplementary standardized random-effects model produces the same broad sign pattern for the key financing variables, which strengthens confidence in the stability of the findings.

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The economic message is clear. In the AI industry, the structure of finance matters more than the simple existence of finance. Funding channels that can bear uncertainty and support long-horizon innovation appear more consistent with productivity upgrading, while conventional credit and accumulated internal funds show weaker links in the observed sample. This implies that science and technology finance should be redesigned around fit, timing, and allocation efficiency. For policy, the central task is to connect subsidies, equity capital, and innovation-oriented credit into a more coherent system that matches the real financing needs of AI firms. For research, the next step is to deepen identification through stronger endogeneity strategies and a more explicit decomposition of the NQPF index. Even with those limitations, the present evidence offers a useful firm-level basis for understanding how finance can better support the rise of new quality productive forces in strategic emerging industries.

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