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Artificial Intelligence and Chinese firms' R&D Intensity

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Abstract

The adoption of Artificial Intelligence (AI) not only induces substantial corporate research and development input but also enhances firms' output and productivity, thereby sales. This study examines the impact of AI on firms' R&D intensity, the ratio of corporate R&D investment and sales. Using data from China's A-share listed firms from 2010 to 2024 and employing appropriate econometric methods, this study finds that AI significantly increases corporate R&D intensity, which suggests that more resources are allocated to R&D activities because of the adoption of artificial intelligence. Furthermore, the study identifies two key mechanisms: raising the demand for R&D staff and improving free cash flow.

Keywords: AI, R&D intensity, skilled labor, productivity
Jel codes: O12, O16, D24

1. Introduction

The rapid advancement of artificial intelligence (AI) has spurred intense debate about its economic impact. Although AI is widely recognized as a transformative General Purpose Technology (GPT) (Antonioli et al., 2024; Noy and Zhang, 2023), its economic contributions are probably overestimated (Acemoglu, 2025; Chen, 2021).

To gain a deeper understanding of such topic, I develop a theoretical framework that captures the mechanisms of how AI affects firms' R&D intensity and provide several testable hypotheses. I then empirically test these hypotheses using data from Chinese A-share listed firms from 2010–2024. The main finding indicates that AI significantly increases firm R&D intensity, primarily by raising demand for R&D personnel (high-skilled labor) and augmenting free cash flow. This finding suggests that firms tend to channel AI-driven productivity gains into R&D reinvestment rather than immediate output expansion, providing a micro-level perspective on why the macroeconomic benefits of AI may appear limited.

The central research problem of this article concerns the dynamics encountered during the implementation of the advanced compliance mechanisms established in the Kazakhstani banking sector. The study aims to analyse how governance principles are constructed through financial regulations and to identify the structural obstacles facing compliance processes in the sector. Accordingly, the article first examines the theoretical framework of financial governance, then analyses Kazakhstan's existing regulatory structure, and subsequently focuses on the risks associated with actual implementation processes.

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2. Theoretical Framework

2.1 AI as a General-Purpose Technology

Artificial intelligence is widely recognized as a general-purpose technology (GPT) with the potential to reshape production processes across industries (Antonioli et al., 2024; Noy & Zhang, 2023). Unlike prior automation technologies that primarily substituted for routine manual labor, AI extends the frontier of machine capabilities into cognitive and non-routine tasks (Acemoglu, 2025). This distinctive feature suggests that AI's economic impact operates through channels beyond simple labor displacement.

Following the task-based framework developed by Acemoglu (2025) and extended by subsequent studies (Feng et al., 2023; Yao et al., 2024), we conceptualize a firm's production as comprising a continuum of tasks with varying degrees of complexity. Simple, routine tasks can be performed by capital or low-skilled labor, while complex, non-routine tasks require high-skilled labor—particularly R&D personnel. AI technologies fundamentally alter this task allocation in two ways: they automate certain routine tasks previously performed by low-skilled workers, and they simultaneously create new complex tasks that demand high-skilled expertise. This dual effect has profound implications for firms' factor demand and investment behavior.

2.2 AI and the Demand for R&D Personnel

A central mechanism through which AI affects firm behavior is its impact on labor demand structure. As AI automates routine tasks, the relative importance of non-routine, complex tasks increase. These complex tasks−such as developing AI algorithms, managing AI-driven production systems, interpreting data outputs, and innovating new applications−require specialized human capital that is typically embodied in R&D personnel (Yao et al., 2024; Zhang et al., 2024).

Crucially, the implementation and maintenance of AI technologies are themselves R&D-intensive activities. Firms cannot simply adopt AI without corresponding investments in complementary human capital (Chen, 2021). The deployment of AI necessitates hiring data scientists, AI engineers, machine learning specialists, and other R&D-oriented professionals. This creates a skill-biased demand shift: the application of AI expands the set of tasks that require high-skilled labor, thereby increasing firms' demand for R&D personnel (Li et al., 2024).

An increase in R&D personnel, in turn, directly raises R&D expenditure. Under accounting standards, wages and benefits for R&D staff are typically capitalized or expensed as part of R&D input. Moreover, firms with a higher proportion of R&D staff tend to exhibit stronger innovation orientations and are more willing to invest in long-term R&D projects (Lu et al., 2025). Thus, by increasing the demand for R&D personnel, AI stimulates R&D investment.

2.3 AI, Productivity, and Cash Flow

The second mechanism operates through the productivity-enhancing effect of AI. By improving production efficiency, reducing waste, optimizing supply chains, and enabling better decision-making, AI lowers firms' marginal costs of production (Acemoglu, 2025; Feng et al., 2023). Lower marginal costs allow firms to reduce prices, expand output, and increase total revenue. More importantly, cost reductions translate directly into higher operating profits−i.e., free cash flow.

Free cash flow is a critical determinant of R&D investment (Himmelberg & Petersen, 1994; Liu et al., 2024). Unlike external financing, which is subject to information asymmetries, transaction costs, and credit constraints, internal cash flow provides firms with flexible and readily available funds. R&D projects are inherently risky, uncertain, and long-term in nature; they often require sustained financial commitment without immediate returns. Firms with ample free cash flow are better positioned to absorb the associated risks and maintain consistent R&D investment (Zhao, 2017).

Therefore, AI's cost-reducing and profit-enhancing effects improve firms' internal financial positions, which in turn facilitates greater R&D investment. This cash flow mechanism complements the personnel mechanism in driving R&D expenditure.

2.4 AI and R&D Intensity

R&D intensity−defined as the ratio of R&D expenditure to operating revenue−captures the extent to which firms allocate their revenue to innovation activities. The theoretical reasoning above suggests that AI increases R&D intensity through two complementary channels. First, the personnel channel operates directly: AI creates demand for R&D staff, and the associated wage and personnel costs directly increase R&D expenditure. Second, the cash

flow channel operates indirectly: AI improves profitability, and the resulting increase in internal funds enables firms to invest more in R&D.

Both channels lead to higher R&D expenditure. Importantly, the personnel channel reflects a structural shift in firms' labor demand that is unlikely to be offset by revenue growth, as the demand for R&D personnel is a prerequisite for effective AI adoption rather than a mere consequence. The cash flow channel creates a positive feedback loop: improved profitability not only relaxes financial constraints but also reinforces firms' innovation-oriented strategies, leading them to reinvest a substantial portion of AI-driven gains into further R&D activities (Liu et al., 2024; Li et al., 2024).

Thus, AI adoption leads to a net increase in R&D intensity, as firms channel productivity gains and increased R&D personnel into higher R&D investment.

2.5 Hypotheses

Based on the theoretical reasoning above, we propose the following three hypotheses:

H1: AI adoption significantly increases firm R&D intensity.

H2: AI adoption increases R&D intensity by increasing the demand for R&D personnel.

H3: AI adoption increases R&D intensity by improving firm free cash flow.

These hypotheses are empirically tested in the following sections using panel data from Chinese A-share listed firms. H1 corresponds to the baseline regression, while H2 and H3 are examined through mediation analysis.

3. Research Design

3.1 Empirical Specification

I consider the following specification for the empirical investigation (baseline regression and mechanism analysis)

$$RDI_{it+1} = \alpha_0 + \alpha_1 AI_{it} + \sum_{k=1}^{6} \beta_k Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

where RDI_{it+1} is a measure of R&D intensity for firm i in year t+1; AI_{it} is a firm i's application level of AI in year t; Z_{it} is the control variable vector mentioned in the preceding section; μ_i and δ_t at respective are firm fixed effects and time fixed effects; ε_{it} is the term of disturbance, and I cluster the standard errors at the level of firm.

3.2 Data and Variables

Variables

I use R&D intensity to be the main outcome variable. Two ways are often used to compute corporate R&D intensity, which are ($\frac{R\&D\ input}{total\ asset}$) (Xv et al., 2017) and ($\frac{R\&D\ input}{the\ operating\ revenue}$) (Zhang et al., 2012; Zhang and Hao, 2024), I will select the latter to be our main outcome variable in the baseline regression. The reason for choosing R&D intensity to be the dependent variable is that this ratio reflects the extent to which firms allocate their revenue to innovation activities. A rise in R&D intensity indicates that firms are channeling a greater share of their revenue into R&D investment.

Following most of the researchers who examine the problems about firm-level AI technologies (e.g. Yao et al., 2024; Li et al., 2024), I use the frequency of AI technologies related words in a listed firm's annual report to be the core explained variable (AI), the data are acquired in CSMAR database. In the regression model, the natural logarithm of one plus the count of AI-related keywords identified in the reports is used as the proxy for a firm's level of AI technologies.

According to hypothesis 2, the application of AI will create new labor-intensive tasks which can only be performed by R&D personnel, hence, I select the ratio of R&D personnel and total labor (RDPratio) as one of the mediating variables.[1] Another mediating variable in the paper is free cash flow, which is the cash remaining

[1] Actually, if an individual is employed as an R&D staff, it means that he or she is not only Ill-educated but with necessary skills to tackle complex and technical tasks.

after a company covers its reinvestment and working capital needs (Li, 2019).[2] Since AI adoption often requires substantial investment, free cash flow captures the net change in cash available to the firm and accounts for corporate capital expenditures. Therefore, free cash flow is a more suitable metric in this context. To ensure comparability, I follow Zhao's method (Zhao, 2017) to use the indicator of relative free cash flow, which is the ratio of FCF and total assets (FCFTA).

Furthermore, I also include a series of control variables in our regression model: Firm size (Size), measured by the natural logarithm of total assets; Firm Age (Age), measured by the natural logarithm of the number of years between the firm's establishment and the observation year; Return of Assets（ROA）, measured by Net profit / Balance of total assets; Tobin's Q value (TBQ), measured by the sum of the market value of equity and the book value of liabilities, divided by the book value of total assets; Ratio of liabilities (Lev), measured by total liabilities/total assets and the ownership of a firm (State), measured by a dummy variable which equals to 1 when a firm is state-owned, and equals to 0 when a firm is not owned by state.

Data Source and Sample Construction

Our dataset contains data from A-share listed firms over the period of 2010-2024, obtained by merging different firm-level information, using the unique identification number[3] of firms listed in mainland, China. The source of our dataset is CSMAR (China Stock Market & Accounting Research) database. To ensure the information contained in our dataset is reliable, I perform some cleaning to the information I collected: (1) exclude companies that halted public listing, delisted, and I subjected to special treatment (symbolled as ST and *ST); (2) exclude companies in the industries of finance and real estate; (3) exclude enterprise annual samples with numerous missing values; (4) winsorize continuous non-logarithmic variables at 1% to reduce the potential impact of extreme values on the results.

3.3 Descriptive Statistics

Table 1 presents the descriptive statistics for the key variables.

[2] It can be calculated as following equation: FCF= profit before interest and tax×(1-tax rate) +depreciation and amortization-net change in working capital-net capital expenditure.

[3] In our dataset, I denote it as Stkcd.

Table 1. Descriptive Statistics

Variables	Sample Size	Mean	Standard Deviation	Min.	Max.	Median
RDI	30165	0.0520	0.0558	0.0003	0.332	0.0380
AI	30165	1.088	1.301	0	6.503	0.693
FCFTA	30165	-0.0181	0.144	-3.260	23.465	2.776
RDPratio	30165	0.1339	0.1397	0	0.6995	0.1105
Size	30165	22.31	1.306	20.01	26.42	22.102
Age	30165	1.986	0.935	0	3.401	2.079
Lev	30165	0.408	0.202	0.008	3.919	0.400
TBQ	30165	1.989	1.196	0.834	7.767	1.603
ROA	30165	0.035	0.091	-0.248	0.785	0.039
State	30165	0.272	0.445	0	1	0

4. Empirical Results

4.1 Baseline Results

In the baseline regression, before examining the effect of AI on firms' R&D intensity, I separate the variable RDI into 2 variables, which are at respective a firm's R&D input (RDinput) and operating revenue (REV), both are obtained by taking the natural logarithm of annual amount plus one. As shown in the column (1) and (2) of the table 2, the results are significant and under our expectation, the coefficients of RDinput and REV are at respective 0.0431 and 0.0080, suggesting that the adoption of AI can both boost firms' operating revenue, thereby productivity and R&D investment.

The column (3) shows how AI influence corporate R&D intensity. The coefficient of interest is 0.0022, under the significance level of 5%, indicating that AI not only boosts firm revenue but also stimulates R&D investment, leading to a net increase in R&D intensity.

Table 2. Baseline Regression Results

Variables	(1)	(2)	(3)

	ln(Rev)	ln(RDinput)	ln(RDI)
AI	0.0080**	0.0431***	0.0022**
	(0.0036)	(0.0059)	(0.0003)
Control variables	YES	YES	YES
Constant	1.4159***	-0.3864	0.0464***
	(0.2052)	(0.2904)	(0.0110)
Sample Size	30165	30165	30119
Adjusted R^2	0.9635	0.8807	0.8127
Time Fixed Effects	YES	YES	YES
Firm Fixed Effects	YES	YES	YES

4.2 Robustness Tests

Instrumental Variables Approach

As discussed in preceding sections, bidirectional causality issue probably exists in the correlation between our outcome and explained variables: on the one hand, a firm willing to spend higher R&D expenditures is more likely to have higher level application of AI technologies; on the other hand, higher level application of AI technologies can also induce a firm to improve its R&D input. Therefore, I introduce two instrumental variables to eliminate such potential two-way causality problem.

Following previous studies (Li et al., 2024; Han and Chen, 2025), our analysis selects instrumental variables based on both the industry and regional dimensions of firms to mitigate concerns of reverse causality. The first instrumental variable (IV1) is one-year-lagged average AI adoption level of other firms in the same province. The second instrumental variable (IV2) I select is one-year-lagged average AI adoption of other firms in the same industry. On the one hand, a firm's level of AI adoption can easily be influenced by their counterparts in the same industry and province, on the other hand, other features of a firm are convinced to independent of other firms' AI adoption. Hence, both instrumental variables are highly correlated with the firm's own AI level, while independent of the regression model's error term.

Column (1)-(4) in table 3 reports the results of the instrumental variables approach. The results indicate that the coefficient of interest in the first-stage regression is statistically significant at the 1% level. Furthermore, the Kleibergen-Paap rk LM test significantly rejects the null hypothesis of underidentification, suggesting that the model does not suffer from this issue. The Cragg-Donald Wald F statistics are approximately 469.53 and 45.22, which substantially exceed the critical values of the Stock-Yogo Weak instrument test. This suggests that the instrumental variables I select are robust and do not suffer from Weak instruments. Furthermore, I find that the estimated coefficients in the second-stage regression are both statistically and economically significant, suggesting that AI exerts a positive effect on firms' R&D intensity.

Propensity Score Matching (PSM) for Self-Selection Bias

The self-selection bias also needs to be taken into consideration. As it is possible that those larger firms with more sufficient funds are more inclined to adopt and develop AI technologies. Therefore, to mitigate the self-selection bias, I introduce PSM method. Following Han and Chen (2025), I classify our sample into treatment and control groups based on the presence of AI-related keywords in the annual reports. The propensity scores are then estimated via a logistic regression incorporating the control variables specified in Equation (1). This is followed by 1:1 nearest-neighbor matching with replacement. After matching, balance diagnostics show that standardized biases for most covariates fall below 5%. Additionally, t-tests indicate no significant differences

between the groups for these variables, suggesting that the match successfully balanced the observed characteristics and is of high quality.

As shown in Column (5) of Table 5, the coefficient on AI remains positive and significant at the 1% level, confirming that self-selection bias based on observable characteristics does not pose a serious threat to our main results.

Event Study Analysis

In this section, I employ an event study analysis to examine the causal linkage between AI adoption and R&D intensity. The panel event study specification is:

$$RDI_{it} = c + \sum_{l=-5, l\neq -1}^{5} \xi_l \, \mathbb{1}(t - EVENT_i = l) + \sum_{k=1}^{6} \beta_k' Z_{it} + \mu_i + \delta_t + \lambda_s + \varepsilon_{it} \qquad (2)$$

Following the identification strategy in Liu and Ma (2025), I define the adoption year as the year in which a firm first discloses AI-related keywords in its annual report. EVENT_i denotes this first disclosure year for firm. I then define the indicator variables $\mathbb{1}(t - \mathrm{EVENT}_i = l)$, which take the value of one if firm i is at relative year l since AI adoption, and zero otherwise. The outcome and control variables are consistent with the baseline specification. To account for unobserved heterogeneity and industry-specific shocks, I include firm μ_i, year δ_t, and industry λ_s fixed effects. I cluster standard errors at the firm level to account for potential serial correlation across firms.

Existing literature has pointed that TWFE estimators may be biased in the presence of heterogeneous treatment effects over time. To ensure the robustness of our results, I estimate the event-study specification using the robust estimator proposed by Callaway and Sant'Anna (2021). And to ensure that our dynamic estimates are not confounded by sample composition changes, I restrict our analysis to a balanced panel of firms with continuous observations over the event window ($l \in [-5,5]$). This selection mitigates sample composition bias and ensures that the estimated paths of R&D intensity are driven by firm-level adjustments rather than changes in the sample pool.

Figure 1 presents the event study results. I find no statistically significant difference in pre-treatment trends between AI adopters and non-adopters, supporting the parallel trends assumption. By contrast, starting from the current adopting year, adopters exhibit a significantly higher R&D intensity compared to the control group. This finding corroborates the causal link between AI adoption and R&D intensity.

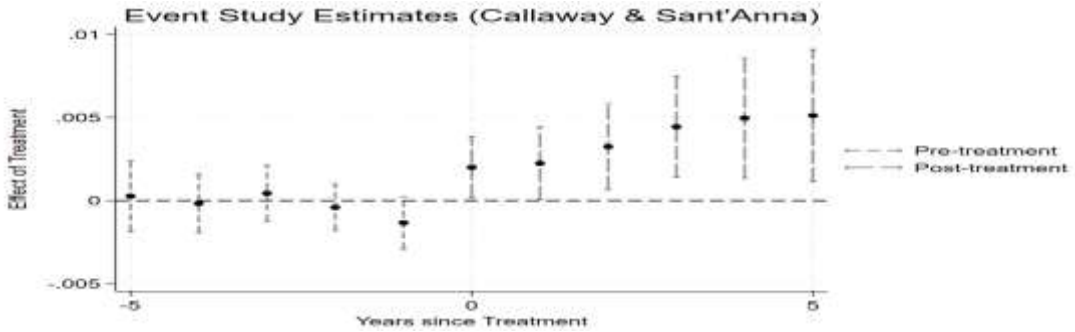

Fig. 1. This figure plots the event-study estimates of the impact of AI adoption on R&D intensity using the Callaway and Sant'Anna (2021) estimator. The analysis accounts for staggered adoption and heterogeneous treatment effects. The reference period is $l = -1$. Error bars indicate 90% confidence intervals.

Controlling for Additional Factors

Our baseline regression includes six firm-level control variables. However, existing literature suggests that factors such as the traits of the senior executive team and provincial characteristics, can also influence a firm's

R&D activities. This implies that our baseline results might be subject to omitted variable bias. To mitigate this concern, I introduce additional controls.

First, following Zhou et al. (2019), I incorporate variables measuring the traits of senior executives. I select four variables from the CSMAR database:

Executive age: the natural logarithm of the average age of senior executives. Education level: an ordinal variable (1 to 6) corresponding to the highest degree attained: 1 = vocational high school or below, 2 = junior college, 3 = bachelor's degree, 4 = master's degree, 5 = doctoral degree, and 6 = other. Overseas experience: a categorical variable (1 = work experience abroad, 2 = study experience abroad, 3 = no overseas experience). And professional title: a dummy variable that equals 1 if an executive holds a professional title.

Second, I control for provincial-level factors by including the logarithm of provincial GDP per capita, the share of the secondary industry's output in provincial GDP, and the logarithm of the number of research institutions in the province. These data are collected from CSMAR and the National Bureau of Statistics (NBS) Website.

As shown in Column (6) of Table 3, though becoming smaller, our coefficient of interest remains statistically significant, indicating that the main findings are robust to the inclusion of these additional variables.

Table 3. Endogenous Discussion

Variables	(1) AI	(2) RDI	(3) AI	(4) RDI	(5) RDI	(6) RDI	(7) RDI
AI		0.0152*** (0.00334)		0.0261** (0.0106)	0.0123*** (0.0010)	0.0020*** (0.0004)	
IV1	0.0175*** (0.00246)						
IV2			0.0175*** (0.00288)				
AIMDA							0.0022** (0.0003)
Control variables	YES	YES	YES	YES	YES	YES	YES
Kleibergen-Paap rk LM	64.899		38.438				
Cragg-Donald Wald F	469.528		45.222				
Sample Size	25640	25640	25726	25726	15999	21293	30119
Time Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES

Replacing Independent Variable

I also adopt the method of Yao et al. (2024) by using the natural logarithm of one plus the word count of artificial intelligence keywords in the Management Discussion and Analysis (MD&A) section as an alternative measure. The result presented in Column (7) of Table 3 also indicates that our findings are robust and reliable.

5 Mechanism Analysis

According to the hypotheses provided in our theoretical model, AI is able to increase a firm's R&D intensity through influencing its labor structure and cash flow. Based on the analysis in the previous sections, I select the share of R&D personnel and the ratio of free cash flow and total assets to be the mediating variables. Both mediating variables are in year t+1. And all the variables right-hand side are the same as the specification in equation (1).

Table 4 presents the results of the mechanism tests. In Column (1), the coefficient of interest is 0.0126 and statistically significant at the 1% level. This implies that a 10% increase in AI adoption is associated with a 12.6% rise in the ratio of R&D personnel, providing empirical support for Hypothesis 2. Columns (2) investigates the impact of AI on free cash flow (FCFTA). The coefficient of interest in Columns (2) is positive and significant at the 5% level. Thus, Hypothesis 2 and 3 are validated.

Table 4. Mechanism Test

Variables	(1) RDPratio	(2) FCFTA
AI	0.0126***	0.026**
	(0.0012)	(0.0012)
Control variables	YES	YES
Constant	-0.1127***	0.3906***
	(0.0394)	(0.0645)
Sample Size	25889	25730
Adjusted R^2	0.8060	0.3213
Time Fixed Effects	YES	YES
Firm Fixed Effects	YES	YES

6 Conclusions

In this paper, I find that AI adoption significantly increases corporate R&D intensity. This effect operates through two distinct mechanisms: raising the ratio of R&D personnel and improving free cash flow. Firms that adopt AI benefit from enhanced productivity, which boosts their revenue; simultaneously, AI adoption stimulates firms to generate higher investment in R&D activities. These findings suggest that firms tend to channel AI-driven gains into innovation reinvestment rather than immediate output expansion.

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