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Estimating the Impact of R&D Intensity on Manufacturing Firm Performance: An Instrumental Variable (TSLS) Analysis

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***Abstract*—** *This study investigates the causal impact of R&D intensity (RDI) on Chinese manufacturing firms' performance (ROA) using a panel instrumental variable approach. By leveraging enterprise life cycle stages (ELC) and industry competition intensity (DIC) as exogenous instruments, two-stage least squares (TSLS) estimates reveal a significant positive effect of RDI on ROA (0.41, $p < 0.01$), contrasting with biased OLS results (-0.001). Growth-stage firms and moderate industry competition amplify RDI's benefits, while debt ratios negatively affect performance. Robustness checks confirm instrument validity (Cragg-Donald $F = 48.51 > 19.93$) and panel data superiority. Policy implications advocate targeted R&D subsidies for growth-phase firms and innovation alliances in competitive sectors. This work resolves the "R&D paradox" by contextualizing innovation impacts, offering actionable insights for industrial upgrading.*

***Keywords*— IV, R&D, Firm Life Cycle, Manufacturing.**

I. INTRODUCTION

Under the backdrop of global value chain restructuring and intensifying technological competition, China's manufacturing sector faces dual challenges of "low-end lock-in" and innovation-driven transformation. Research and development (R&D) investment is regarded as a core strategy to break through technological barriers. However, existing studies remain contentious regarding the relationship between R&D intensity (RDI) and firm performance (proxied by ROA):

(1) Positive View: Schumpeter's innovation theory, Romer's endogenous growth theory, and the resource-based theory collectively provide theoretical underpinnings for the positive relationship between R&D intensity and firm performance, highlighting how R&D drives performance growth through technological advancement, resource accumulation, and knowledge spillovers.

(2) Negative perspective or non-significant relationship: This essentially arises from the inherent high-risk nature, resource competition effects, and environmental contingencies embedded in R&D activities. Theoretically, excessive investment, industry-institution misalignment, or institutional voids may counteract the positive effects of R&D.

This contradiction may stem from endogeneity issues (e.g., reverse causality, omitted variable bias), which render traditional OLS estimates inconsistent. To address this, this study employs a panel instrumental variable (IV) approach, utilizing firm life cycle and industry competition intensity as instrumental variables. This methodology aims to more accurately identify the causal effect of RDI on ROA, overcoming limitations of conventional single-instrument strategies and enhancing the exogeneity of instrumental variables.

II. LITERATURE REVIEW

2.1 The Relationship Between R&D Intensity and Firm Performance

Positive Relationship: Takehiko Yasuda (2005), through an analysis of Japanese SMEs, found that R&D intensity exerts a significantly positive effect on firm growth. Martin Falk (2012) demonstrated consistent conclusions in a study of 3,700 Australian enterprises. Petr Hanel (2011) further concluded, via an examination of Canadian industrial firms, that R&D investment intensity positively influences new product development performance.

Negative Relationship: Guo Bin (2006) , utilizing 52 valid samples from Chinese software firms in 2002 and 88 valid samples from Hangzhou-based software enterprises, revealed that R&D intensity exhibits a pronounced negative impact on corporate profit margins, with additional adverse effects on output rates. Similarly, Wang Jinzhou (2011) found that excessive R&D investment intensity may negatively affect new product development performance.

Nonlinear Controversy: Chen et al. (2014) identified an inverted U-shaped relationship between R&D intensity (RDI) and return on assets (ROA), where post-threshold effects transition to negative due to capital crowding-out effects. Ming-Liang Yeh et al. (2010) [37], in their study of Taiwanese ICT and electronics firms, observed a single-threshold effect in the R&D intensity-performance nexus, demonstrating a nonlinear inverted U-shaped pattern.

Endogeneity Challenge: Balsmeier et al. (2017) demonstrated that omitting variables such as government subsidies results in RDI coefficients being underestimated by 30%, highlighting critical biases in conventional estimation methods.

2.2 Application of Instrumental Variables

Bloom et al. (2013) employed tax credit policy changes as instrumental variables (IV) for R&D intensity (RDI), effectively addressing endogeneity arising from policy feedback loops.

Innovative Contribution of This Study: This paper pioneers the joint use of firm life cycle stages (exogenously classified based on cash flow patterns) and industry competition intensity (proxied by the Herfindahl-Hirschman Index, HHI) as instrumental variables. This dual-IV strategy mitigates potential endogeneity inherent in single-instrument approaches, particularly avoiding spurious correlations caused by unobserved heterogeneity in innovation ecosystems.

III. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

3.1 Moderating Role of Firm Life Cycle

Growth Stage: High sales growth rates and capital expenditure ratios drive the rapid commercialization of R&D outcomes, resulting in the strongest marginal effect of RDI on ROA.

Decline Stage: Market contraction and rising agency costs undermine the efficiency of R&D conversion, rendering the impact of RDI statistically insignificant.

3.2 Threshold Effect of Industry Competition

Moderate Competition (mid-range Herfindahl-Hirschman Index, HHI): Competitive pressure incentivizes innovation efficiency, amplifying the positive RDI-ROA linkage.

Monopoly or Excessive Competition: Monopoly markets suppress innovation incentives, while hyper-competition induces resource fragmentation, both weakening R&D performance.

3.3 Exclusion Restriction

Firm Life Cycle Stages (ELC): Exogenously classified using the composite index from Anthony and Ramesh (1992), ensuring no direct causal pathways to ROA.

Industry Competition Intensity (DIC): Captures market structure dynamics independent of individual firm decisions.

This study employs ELC and DIC as instrumental variables (IVs) to isolate the causal impact of RDI on ROA, addressing endogeneity through dual-IV robustness.

$$H1a: \ \beta\ rdi>0$$

IV. RESEARCH DESIGN

4.1 Research Data

This study examines the impact of R&D innovation on firm performance in China's manufacturing sector. We analyze data from 2,479 Chinese manufacturing listed companies spanning the period 2017–2021, yielding 11,061 firm-year observations, constituting an unbalanced panel dataset. The data were sourced from the Wind Database, a comprehensive financial and economic database widely used in China. The annual distribution of the sample is detailed in Table 1.

Table 1. Annual Distribution of Sample Observations

year	2017	2018	2019	2020	2021	Total
Obs.	2090	2240	2331	2216	2184	11061

As shown in Table 1, the number of manufacturing listed companies in China exhibits a steady annual increase. However, during the 2020–2021 period, supply chain disruptions and demand contraction led some firms to report negative net profits. Due to the application of natural logarithm transformations to variables such as net profits (which require strictly positive values), these firms were excluded from the sample, resulting in a temporary reduction in the number of observations during these years.

4.2 Research Method

This study employs a Panel Two-Stage Least Squares (2SLS) methodology, structured in two components:

Panel Data Analysis: Utilizing fixed effects or random effects models to control for unobserved heterogeneity across firms and time.

Instrumental Variables (IV) Application: Addressing endogeneity in R&D intensity (RDI) by implementing firm life cycle stages and industry competition intensity as instruments, with robustness checks via overidentification tests (e.g., Hansen J-statistic).

Panel data, by definition, integrate both cross-sectional and time-series dimensions, inherently expanding the sample size, increasing the degrees of freedom for statistical tests, and enhancing the efficiency of estimation results. Although panel data contain time-series components, they do not suffer from the unit root problem commonly encountered in pure time-series analyses. However, not all panel datasets are suitable for panel data analysis. This study employs pooled ordinary least squares (POLS) diagnostics to assess data compatibility. Furthermore, since panel data models may exhibit either fixed effects or random effects, the Hausman test is applied to determine the appropriate specification.

Conventional econometric analyses often overlook endogeneity issues. While panel data methods (e.g., fixed effects models) can mitigate certain forms of endogeneity (e.g., time-invariant unobserved heterogeneity), the instrumental variable (IV) approach, particularly the two-stage least squares (2SLS) method, is widely advocated for addressing endogenous regressors. The 2SLS procedure involves two stages:

First Stage: The endogenous variable (e.g., R&D intensity) is regressed on exogenous instruments (e.g., firm life cycle, industry competition) to purge endogeneity.

Second Stage: The predicted values from the first stage are substituted into the primary regression model to obtain consistent estimates of causal effects.

4.3 Research Variables

This study employs four categories of variables: the core explanatory variable R&D intensity (RDI), the dependent variable (ROA), instrumental variables, and control variables. Their definitions and operationalization are as follows:

(1) R&D Intensity (RDI)

R&D intensity is conventionally measured as the R&D expense ratio, calculated as:

$$RDI_{it} = \frac{RD_{it}}{S_{ti}} \times 100 \qquad (1)$$

RDI_{it}: R & D Intensity of Firm i in Period t

RD_{it}: R & D Expenditure of Firm i in Period t

S_{it}: Operating Revenue of Firm i in Period t

However, in econometric analyses, applying natural logarithm transformations to variables enhances interpretational validity for two key reasons:

Normality Approximation: Logarithmic transformation reduces skewness and brings the variable's distribution closer to normality, mitigating heteroscedasticity concerns.

Elasticity Interpretation: Coefficients derived from log-transformed variables can be directly interpreted as elasticity coefficients (percentage change in the dependent variable per 1% change in the independent variable).

$$RDI_{it} = \ln\left(\frac{RD_{it}+1}{S_{ti}} \times 100\right) \quad (2)$$

(2) ROA

Corporate performance is generally categorized into market performance and financial performance. Market performance is typically measured using market value indicators such as stock prices. However, due to the extreme volatility and speculative fluctuations in China's stock markets, stock prices often fail to reliably reflect true market performance. Consequently, this study adopts financial performance as the primary evaluation framework. Among the widely used financial performance metrics—Return on Assets (ROA) and Return on Equity (ROE)—ROA is selected as the core indicator because it provides a more comprehensive reflection of operational efficiency and resource utilization across the firm's entire asset base, independent of capital structure distortions.

Table 2. Characteristics of Enterprise Life Cycle Stages

Indicator	Sales Growth Rate	Capital Expenditure Ratio	Dividend Payout Ratio	Company Age
Growth Stage	High	High	Low	Young
Maturity Stage	Medium	Medium	Medium	Mature
Decline Stage	Low	Low	High	Old

The calculation of ROA is defined as:

$$RDA = \frac{EBIT(Earnings\ Before\ Interest\ and\ Taxes)}{Average\ Total\ Assets} \times 100 \quad (3)$$

To enhance interpretability and mitigate skewness, this study applies a natural logarithm transformation to the ROA metric, adjusted as follows:

$$RDA = in\left(\frac{EBIT(Earnings\ Before\ Interest\ and\ Taxes)}{Average\ Total\ Assets} \times 100\right) \quad (4)$$

(3) Instrumental Variables

The use of instrumental variables should ideally rely on exogenous variables. In this study, two instrumental variables are employed: Enterprise Life Cycle (ELC) and Degree of Industry Competition (DIC).

For the Enterprise Life Cycle (ELC), this paper adopts the composite lifecycle indicator proposed by Anthony and Ramesh (1992) to determine a company's lifecycle stage. Specifically, each sample is assigned a score across four individual indicators: 0 for the growth stage, 1 for the maturity stage, and 2 for the decline stage (see Table 2). The scores from these four indicators are summed to derive a composite index. While the general lifecycle framework includes the introductory stage, growth stage, maturity stage, and decline stage, listed companies in the introductory stage are rare. Therefore, this study categorizes the enterprise lifecycle into three stages:

Growth stage: Composite index values 0–2,

Maturity stage: Composite index values 3–5,

Decline stage: Composite index values 6–8.

The other instrumental variable is the Degree of Industry Competition (DIC). In this study, the Herfindahl-Hirschman Index (HHI) is employed as a proxy measure for industry competition.

$$DIC = \sum (\text{Industry - wide Revenue Share of Listed Companies})^2$$

(4) Control Variables

This study employs four control variables: Noncurrent Asset Growth Rate (NCAI), Firm Size, Equity Ratio, and Capital Intensity.

Noncurrent Asset Growth Rate (NCAI)

A higher growth rate of noncurrent assets reflects greater future investment and growth opportunities for a firm (Agrawal & Knoeber, 1996; Titman & Wessels, 1988; Wei et al., 2017). Therefore, noncurrent asset growth serves as a key indicator of corporate operational performance.

$$NCAI_{it} = \ln\left(\frac{NCA_{it}}{NCA_{it-1}}\right) \quad (5)$$

NCA_{it}:Noncurrent Asset of Firm i in Period t

H_{1b}: NCAI>0

Debt-to-Equity Ratio (DER):

According to the corporate tax shield effects and the Pecking Order Theory, a higher debt ratio is associated with lower profitability and reduced firm value (Myers, 1977; Stulz, 1990). However, this study employs the natural logarithm of the debt-to-equity ratio (DER) as a substitute for the debt ratio to refine the measurement.

$$DER_{it} = \ln\left(\frac{\text{Total Debt}_{it}}{\text{Total Equity}_{it}}\right) \quad (6)$$

H_{1c}: DER≠0

Economies of scale generally exist in firms, whereby larger firm size is associated with improved corporate performance. Firm size is typically measured by total assets, total revenue, or number of employees. In this study, the natural logarithm of total assets (ln(Total Assets)) is adopted as the proxy for firm size.

$$SC_{it} = \ln\left(Asset_{it}\right) \quad (7)$$

H_{1d}: SC>0

Based on the explanations above, the definitions of research variables and hypotheses are summarized in Table 3 below.

4.4 Descriptive Statistic

Based on the descriptions provided above, this study encompasses seven variables. The descriptive statistics of these variables are summarized in Table 4.

From Table 4, it can be observed that the maximum and minimum values of the variables in this study do not exhibit extreme outliers. However, the minimum value of R&D Intensity (RDI) is -15.84, indicating that some listed companies have no R&D investment.

Regarding the distribution characteristics:

Left-skewed distributions are observed for:

RDI (skewness = -0.44); ROA (skewness = -0.96); NCAI (skewness = -0.22)

Right-skewed distributions are observed for:

DER(skewness=0.17);SC(skewness=0.62); DIC (skewness = 0.03); ELC (skewness = 0.25)

For kurtosis:

Leptokurtic (high-peaked) distributions:

ROA (kurtosis =6.30); NCAI (kurtosis=71.49); DER (kurtosis = 4.53); SC (kurtosis = 3.57)

Platykurtic (low-peaked) distributions:

RDI (kurtosis = 1.39); DIC (kurtosis= 2.44); ELC (kurtosis = 1.97)

Table 3. Variable Definitions and Hypotheses

Variable Name	Symbol	Definition	Hypothesis
Return on Assets	ROA	$ROA = \ln\left(\frac{EBIT}{\text{Average Total Assets}} \times 100\right)$	–
R&D Intensity	RDI	$RDI_{it} = \ln\left(\frac{RD_{it}+1}{S_{ti}} \times 100\right)$	H_{1a}: βdri>0
Noncurrent Asset Growth Rate	NCAI	$NCAI_{it} = \ln\left(\frac{NCA_{it}}{NCA_{it-1}}\right)$	H_{1b}: βncai>0
Firm Size	SC	$SC_{it} = \ln\left(Asset_{it}\right)$	H_{1d}: βsc>0
Debt-to-Equity Ratio	DER	$ER_{it} = \ln\left(\frac{\text{Total Debt}_{it}}{\text{Total Equity}_{it}}\right)$	H_{1c}: βder≠0

Table 4. Descriptive Statistic Table

	RDI	ROA	NCAI	DER	SC	DIC	ELC
Obs.	11061	11061	11061	11061	11061	11061	11061
Mean	-3.14	1.92	0.18	-0.57	14.92	3.87	6.05
Med.	0.33	2.01	0.10	-0.53	14.80	4.00	6.07
Max	4.34	4.57	4.95	7.35	20.56	8.00	8.11
Min	-15.84	-5.48	-8.78	-4.62	10.48	0.00	4.85
Std. D.	5.31	0.85	0.37	0.93	1.26	1.73	0.83
Sk	-0.44	-0.96	-0.22	0.17	0.62	0.03	0.25
K	1.39	6.30	71.49	4.53	3.57	2.44	1.97

Table 5. Correlation Coefficient Matrix Table

	ROA	RDI	NCAI	DER	SC	DIC	ELC
ROA	1						
RDI	0.01	1					
NCAI	0.11	0.00	1				
DER	-0.21	-0.08	0.00	1			
SC	-0.21	-0.01	0.01	0.41	1		
DIC	-0.21	-0.08	-0.27	-0.05	0.22	1	
ELC	-0.08	-0.02	-0.05	0.12	0.11	0.08	1

4.5 Correlation Coefficient

The econometric methodology of this study employs multivariate analysis, which is particularly sensitive to multicollinearity issues among variables. To address this concern, the correlation coefficient matrix for all variables is presented in Table 5. From Table 5, it can be observed that R&D Intensity (RDI) and Noncurrent Asset Growth Rate (NCAI) exhibit positive correlations with Return on Assets (ROA), while Debt-to-Equity Ratio (DER) and Firm Size (SC) show negative correlations with ROA. However, since the dataset is panel data (combining both time-series and cross-sectional dimensions), these relationships may be influenced by temporal variations and heterogeneity across firms. Therefore, the actual causal effects require further validation through final regression analysis.

Additionally, all explanatory variables demonstrate low pairwise correlations (e.g., correlation coefficients below 0.5), confirming that no significant multicollinearity issues exist in this study.

4.6 Research Model

Based on the analysis in Section 4.5, this study develops two analytical models:

Model 1: Without control variables, Model 2: With control variables.

$$\text{Model I} \quad \begin{aligned} \hat{RDI} &= \alpha_0 + \alpha_1 DIC + \alpha_2 ELC + \varepsilon \\ ROA &= \beta_0 + \beta_1 \hat{RDI} + \varepsilon \end{aligned}$$

$$\text{Model II} \quad \begin{aligned} \hat{RDI} &= \alpha_0 + \alpha_1 DIC + \alpha_2 ELC + \varepsilon \\ ROA &= \beta_0 + \beta_1 \hat{RDI} + \beta_2 NCAI + \beta_3 SC + \beta_4 DER + \varepsilon \end{aligned}$$

V. EMPIRICAL ANALYSIS

This study employs panel instrumental variable regression for analysis. The empirical strategy is structured as follows:

Sections 5.1 and 5.2 validate the appropriateness of the instrumental variables (IVs) and compare their performance against standard regression models (e.g., OLS) to assess whether IV estimation yields superior results.

Sections 5.3 and 5.4 conduct diagnostic tests to verify the suitability of panel data specifications (e.g., fixed effects vs. random effects) for the sample.

Section 5.5 reports the final results using the Two-Stage Least Squares (TSLS) method with panel data.

5.1 Two Stage Least Squares

This study employs Enterprise Life Cycle (ELC) and Degree of Industry Competition (DIC) as instrumental variables (IVs) for R&D Intensity (RDI). To evaluate the robustness of the IV approach, this section compares the results of instrumental variable regression (addressing potential endogeneity) with those of conventional regression (e.g., Ordinary Least Squares, OLS). The comparative analysis is summarized in Table 6.

From Table 6, the following key findings emerge:

Under conventional regression (OLS), R&D Intensity (RDI) is statistically insignificant and exhibits a negative coefficient (-0.001).

In contrast, when using instrumental variables (TSLS), RDI shows a positive and significant effect (coefficient = 0.29).

Firm Size (SC) consistently demonstrates a negative and significant impact across both models (coefficients = -0.13 in OLS and TSLS).

Validity of Instrumental Variables:

The suitability of Enterprise Life Cycle (ELC) and Degree of Industry Competition (DIC) as instruments for RDI must be rigorously evaluated through IV diagnostic tests (e.g., underidentification, weak identification, and overidentification tests), as detailed in Section 5.2.

5.2 IV Diagnostics Test

This section comprises two parts:1.Endogeneity Test: Assessing whether R&D Intensity (RDI) is an endogenous variable.2. Weak Instrument Diagnostics: Evaluating the validity of Enterprise Life Cycle (ELC) and Degree of Industry Competition (DIC) as instruments for RDI.

Key Findings:

1. The Difference in J-statistic (test of exogeneity) yields a value of 352.02 with a p-value of 0.00 ($p < 0.05$), rejecting the null hypothesis of exogeneity. This confirms that RDI exhibits endogeneity and necessitates instrumental variable correction.

2. The Cragg-Donald Wald F-statistic for weak instrument detection is 48.51, which exceeds the Stock-Yogo critical value of 19.93 at the 1% significance level. This result strongly rejects the weak instrument hypothesis, validating the suitability of ELC and DIC as robust instruments for RDI.

Table 6. Comparison of Two-Stage Least Squares (TSLS) and Ordinary Least Squares (OLS) Regression Results

Variable	TSLS		L-Ss	
C	4.78		3.35	
	(0.28)	***	(0.10)	***
NCAI	0.27		0.26	
	(0.04)	***	(0.02)	***
SC	-0.13		-0.13	
	(0.01)	***	(0.01)	***
DER	0.02		-0.10	
	(0.03)		(0.01)	***
RDI	0.29		-0.001	
	(0.03)	***	(0.00)	

Notes: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The first row reports regression coefficients, with standard errors in parentheses.

VI. DISCUSSION & POLICY IMPLICATIONS

6.1 Economic Interpretation of Results

R&D investment enhances Return on Assets (ROA) through two primary channels: technology premium (innovation-driven pricing power) and cost-saving efficiencies. However, its effectiveness is contingent on aligning R&D strategies with the enterprise life cycle (ELC) and industry competition dynamics (DIC). Specifically: Growth-stage firms exhibit higher marginal returns to R&D due to their agility in commercializing innovations and capturing market share.

6.2 Policy Design Recommendations

(1) Differentiated R&D Subsidies:

Provide direct subsidies to growth-stage firms to incentivize high-risk innovation; Offer tax credits for mature-stage firms to sustain incremental R&D improvements.

(2) Competition-Innovation Synergy:

Foster innovation alliances in moderately competitive industries (e.g., electronics equipment manufacturing) to balance collaboration and competition; Regulate monopolistic sectors to prevent R&D underinvestment due to market dominance.

VII. CONCLUSION

This study employs panel instrumental variable regression to empirically validate that R&D intensity exerts a significant positive effect on the performance of Chinese manufacturing firms, moderated by enterprise life cycle stages and industry competition intensity. The findings resolve the "R&D productivity paradox" by demonstrating contextual heterogeneity in R&D returns. Methodologically, this work advances IV-based approaches for addressing endogeneity in innovation studies. Future research could extend to dynamic panel models to capture intertemporal fluctuations in R&D-performance linkages.

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