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The Impact of Tax Incentives, Government Funding, and R&D Investments on the Innovation Effectiveness of Chinese High-Tech Companies

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ABSTRACT

Tax incentives, government funding, and R&D investments are pivotal policy and internal drivers of innovation in Chinese high-tech firms, as they facilitate technological progress, resource accumulation, and enhanced innovation effectiveness. However, existing studies lack clarity about their specific mechanisms, empirical links to innovation effectiveness, and targeted verification using large-sample panel data. This study empirically tests the direct positive relationships between innovation effectiveness and key factors among Chinese high-tech enterprises, providing theoretical and practical support for policy optimization and enterprise innovation management. Based on the CSMAR database, 347 high-tech firms were selected, yielding 2,082 annual observations from 2019 to 2024. A quantitative approach combining panel data and time-series analysis is adopted, with SPSS for OLS regression and EViews for dynamic trend exploration. Diagnostic and robustness tests are conducted to ensure the validity of the results. Empirical results confirm their significant positive impacts: tax incentives cut R&D costs; government funding offsets market failures; R&D investments strengthen independent innovation capability. Stable variable trends verify the robustness of the result. This study enriches the literature, provides implications for policymakers and managers, and proposes future research directions.

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1. INTRODUCTION

Amid fierce global technological competition, high-tech industries are the core of economic growth and national competitiveness. China is the world's second-largest economy and wants to shift from a "manufacturing powerhouse" to a "technology powerhouse" (Kennedy, 2018). China's high-tech sector has grown rapidly over the past 20 years thanks to effective policies, significant investments in research and development, tax breaks, and government support. The National Medium- and Long-Term Program of Scientific and Technological Development (2006–2020), Made in China 2025 (State Council, 2015), and the 14th Five-Year Plan (NDRC, 2021) have all helped increase research and development (R&D) and patents. The share of high-tech manufacturing in GDP rose from 12% in 2012 to 15% in 2020 (National Bureau of Statistics, 2021). China's spending on research and development has grown by more than 18% every year since 2000, and by 2024, it will be 2.64% of GDP (National Bureau of Statistics, 2025), which is close to the OECD average. Since 2011, China has filed the most patent applications worldwide (Tian et al., 2020), and its GII ranking has risen from 14th (2019) to 11th (2024) (Hammer & Yusuf, 2020; GII, 2024).

Despite significant R&D spending and progress on the GII, TFP has remained unchanged at 0.5%–1% (Cao et al., 2020), which is lower than that achieved by advanced and some middle-income economies (Kennedy, 2020; OECD, 2024). Many high-tech companies are seeing their return on assets (ROA) decline even as they obtain more patents (Cao et al., 2020). This is because their core sectors are not keeping pace with global trends (Chen et al., 2018), resulting in an "innovation effectiveness gap" (Cao et al., 2020; Hammer & Yusuf, 2020). This is because laws put more emphasis on the number of patents than the quality of patents (Lin et al., 2022), there isn't enough radical innovation (Wan et al., 2022; Yu et al., 2021), and tax and funding policies that work for everyone (Dai & Chapman, 2021; Wan et al., 2022). Existing studies mostly focus on the independent impact of a single factor, such as tax incentives, government funding, or R&D investments, on enterprise innovation, while neglecting the synergistic effects of these three key drivers. There is a lack of comprehensive empirical analysis that simultaneously examines how tax incentives, government funding, and internal R&D investments interact and jointly shape innovation effectiveness, leaving a critical research gap in understanding the combined mechanisms of external policy tools and internal investment decisions for high-tech firms. Consequently, it is imperative to elucidate the influence of tax incentives, government funding, and R&D investments on the efficacy of innovation (Li, 2022; Xie et al., 2022).

2. THEORETICAL BASIS AND HYPOTHESIS DEVELOPMENT

2.1 Tax Incentives and Innovation Effectiveness

Tax incentives are designed to lower research and development costs and encourage innovation by providing businesses with financial incentives. Resource-based theory (RBV) views them as VRIN resources that enhance innovation capabilities (Barney, 1991), and dynamic capabilities theory (Teece et al., 1997) holds that they provide businesses with financial slack to build their sensing, seizing, and transforming capabilities. Empirical research validates their beneficial effects: Tian et al. (2020) discovered that tax incentives enhanced R&D, new product sales, and patent acquisition; Dai & Chapman (2021)

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showed that HNTE tax benefits encouraged R&D and patenting; Wan et al. (2022) revealed that preferential policies alleviated tax burdens and refined innovation processes.

This study posits the initial hypothesis grounded in theoretical arguments and empirical evidence:

H1: There is a significant positive relationship between tax incentives and the innovation effectiveness of Chinese high-tech companies.

2.2 Government Funding and Innovation Effectiveness

Government funding provides direct support for high-risk R&D and strategic technologies to address market failures. RBV calls these VRIN resources (Barney, 1991), and dynamic capabilities theory views them as means to foster adaptive capabilities (Teece et al., 1997). This is backed up by research done in China: Yu et al. (2021) discovered that government grants expedited R&D and innovation efficacy; Zhu et al. (2020) observed that grant recipients exhibited elevated ROA and enhanced new product development; Ghazinoory & Hashemi (2021) identified that funding augmented profit margins and innovation. Consequently, H2 posits a large positive correlation between government investment and the innovative efficacy of Chinese high-tech enterprises.

This study posits the second hypothesis, grounded in theoretical arguments and empirical evidence:

H2: There is a significant positive relationship between government funding and the innovation effectiveness of Chinese high-tech companies.

2.3 R&D Investments and Innovation Effectiveness

Research and development (R&D) investment is a significant internal driver that helps with knowledge accumulation, technology development, and resource integration. The resource-based view (RBV) holds that it builds VRIN resources (Barney, 1991), and the dynamic capabilities theory holds that it helps improve adaptive skills (Teece et al., 1997). Empirical research substantiates its beneficial effects: Liu and Dong (2022) found that R&D spending enhanced innovation in high-tech firms; Zhang et al. (2022) noted its direct and indirect impacts via absorptive capacity; and Pan et al. (2021) found that it motivated innovation effectiveness. Thus, H3 is proposed: There is a significant positive relationship between R&D investments and innovation effectiveness of Chinese high-tech companies.

Based on these theoretical arguments and empirical findings, this study proposes the third hypothesis:

H3: There is a significant positive relationship between R&D investments and the innovation effectiveness of Chinese high-tech companies.

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The relationships between these constructs are explained by the model design in Figure 1.

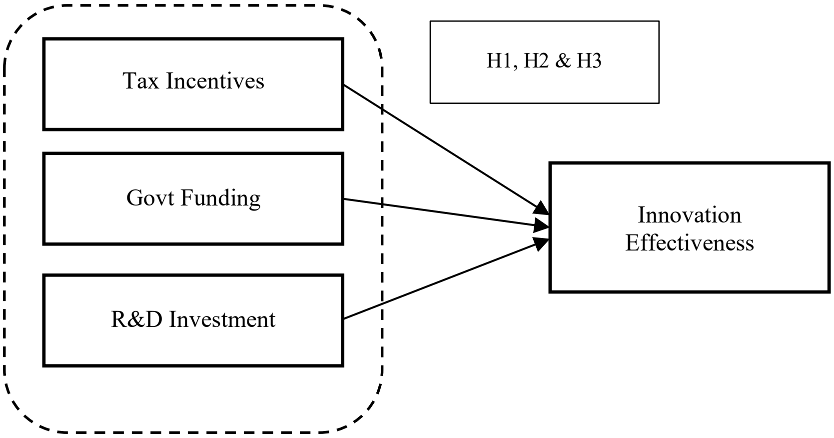

Figure 1: The Conceptual Framework
Source: Author's own data

3. RESEARCH METHODOLOGY AND DESIGN

3.1 Population and Sampling

3.1.1 Population

The target population comprises high-tech companies in China, categorized according to definitions set by the Ministry of Finance and the China National Bureau of Statistics. These companies work in important fields like electronics and information technology, bioengineering and medicine, new energy, new materials, and advanced manufacturing—prioritized under China's "Made in China 2025" and 14th Five-Year Plan.

3.1.2 Sampling Frame and Sampling Method

The sampling frame is drawn from the China Stock Market and Accounting Research (CSMAR) database, the largest and most reliable financial database for Chinese listed companies. A purposive sampling method is used to choose companies that are listed on the Shanghai Stock Exchange, Shenzhen Stock Exchange, or STAR Board between 2019 and 2024, are classified as high-tech companies by the Ministry of Science and Technology (MOST), or have R&D intensity >5% (Yu et al., 2021), and have complete financial, R&D, and innovation data for 2019–2024.

3.1.3 Sample Size and Data Screening

The initial sample consisted of 523 listed high-tech firms. Data screening was performed to exclude firms with missing key variables (e.g., R&D expenditure and patent data for two or more consecutive years), ST/*T firms experiencing financial distress to prevent estimation bias, and those reclassified into

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non-high-tech sectors, including traditional manufacturing. The final sample includes 347 firms and 2,082 firm-year observations covering 2019–2024, which provides adequate statistical power for regression analysis (Hair et al., 2017). Due to a small number of missing values in some variables, the final effective sample for principal regression analysis is 2082 annual observations from enterprises. In the subsequent robustness test, observations that were severely affected by the epidemic from 2020 to 2022 were excluded, leaving 1249 valid observations.

3.2 Data Collection Sources

3.2.1 Primary data sources

Primary data is limited, as the study relies on secondary data for objectivity and replicability. However, patent data (a component of innovation effectiveness) is cross-validated with the State Intellectual Property Office (SIPO) database to ensure accuracy.

3.2.2 Secondary Data Sources

Key data sources comprise the CSMAR Database, which provides financial indicators including tax payments, government funding, R&D expenditure, total assets, liabilities and sales, as well as ownership structure and foreign investment ratio, the SIPO Database offering high-value PCT patent data for measuring innovation effectiveness, annual reports from which new product sales data are manually extracted to support the composite innovation effectiveness indicator, and official publications from MOST and STA supplying policy documents and tax incentive eligibility criteria for verifying HNTE status. Data extraction and cleaning were conducted in Excel and Stata 17.0, with missing values addressed using linear interpolation for time-series gaps and mean substitution for isolated missing values.

3.3 Operationalization of Variables

A tax incentive is "an aspect of a country's tax code designed to incentivize or encourage a particular economic activity by reducing tax payments for a company in the said country" (Chen et al., 2021, p. 7). High-tech firms in China can receive tax incentives under Article 3(a) of the Corporate Income Tax Law for high- and new-technology enterprises (HNTEs). This study will use the firm's annual reports to determine whether it received tax incentives over the past 6 years.

Government funding is "a public instrument used to correct market failure, increase private R&D effort, optimize resource allocation, and facilitate innovation" (Ghazinoory & Hashemi, 2021, p. 19). High-tech firms in China can obtain government funding under the Corporate Income Tax Law for high- and new-technology enterprises (HNTEs). This study will use the firm's annual reports to determine whether it received government funding over the past 6 years.

R&D investment is "a proportion of input, including human and material resources that have been invested for activities of R&D to produce outputs with resources having economic values, such as human resources, facility, capital, and time (Kim et al., 2018, p. 49). Companies in the CSMAR must tell the government how much revenue they generate, how much they spend on research and development, how many patents they hold, how many employees they have, and what their legal representative is like (Liu & Dong, 2022). In this study, R&D investment will be measured using the R&D expenditures of the selected firms, as recommended by Liu and Dong (2022).

Innovation effectiveness refers to "the use of scientific and technological knowledge to create new technologies that form the basis of new products or processes within the firm" (Li, 2022, p. 1289). This study uses the total number of patent applications as the core measurement indicator of innovation efficiency. This indicator can promptly reflect the current level of enterprise innovation output and avoid the lag problem in patent authorization. It is widely used in research on innovation of Chinese high-tech enterprises (Tian et al., 2020; Xiao et al., 2023). At the same time, this study uses new product sales as an alternative indicator for robustness testing, and the results are consistent.

Control variables are those that may explain variance in the dependent variables, as shown by previous research (Zhang et al., 2022). This study identifies six control variables derived from existing literature and pertinent academic research, including the selection criteria and measurement indicators for each variable as follows:

a. The largest shareholder's shareholding ratio, a traditional control variable in corporate innovation research, is utilized based on the research frameworks established by prior scholars, serving to indicate the level of corporate equity concentration and quantified by the initial shareholding proportion.

b. Asset liability ratio, referring to the research conclusions of financial and innovation-related studies, is included to measure the corporate financial leverage and solvency, and it is operationalized by the ratio of total liabilities to total assets.

c. Total assets of ln, with reference to Song et al. (2020), Walter et al. (2022a), and Xiao et al. (2023), are used to supplement the measurement of firm size and avoid deviations from a single indicator, measured by the logarithmic conversion value of total assets.

d. Foreign investment ratio, in line with the research design of existing empirical studies, is included to reflect the impact of foreign capital participation on corporate innovation, measured by the original value of foreign investment proportion.

e. Total number of employees in ln, referring to Xie et al. (2022) and Zhou et al. (2021), is another indicator to measure firm size, operationalized by the logarithmic conversion value of the total number of full-time employees.

f. Nature of Property Rights, with reference to Tian et al. (2020), is used to distinguish between state-owned and non-state-owned enterprises, measured by dummy variables (1 for one type of property right, 0 for the other).

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These control variables effectively control for irrelevant factors, thereby improving the reliability and robustness of the empirical results.

Table 1. Summarising Variables

No.	Variable Name	Variable type	Type of data
1	Tax incentives	Independent variable	Secondary data
2	Government funding	Independent variable	Secondary data
3	R&D investment	Independent variable	Secondary data
4	Innovation Effectiveness（Total number of patent applications）	Dependent variable	Secondary data
5	The largest shareholder's shareholding ratio	Control variable	Secondary data
	Asset liability ratio		
	Total assets of In		
	Foreign investment ratio		
	Total number of employees in In		

Source: Author's own data

3.4 Model Validation

This study constructs the following multiple regression models to test the hypotheses:

$$IE_{i,t} = \beta_0 + \beta_1 Tax_{i,t} + \beta_\lambda \sum Controls_{i,t} + \varepsilon_{i,t}$$
$$IE_{i,t} = \beta_0 + \beta_1 Gov_{i,t} + \beta_\lambda \sum Controls_{i,t} + \varepsilon_{i,t}$$
$$IE_{i,t} = \beta_0 + \beta_1 RD_{i,t} + \beta_\lambda \sum Controls_{i,t} + \varepsilon_{i,t}$$

Where Controls represents the set of all control variables, and the definitions of other variables are shown in Table 1. Model (1) is the regression for testing Hypothesis 1, Model (2) is the regression for testing Hypothesis 2, and Model (3) is the regression for testing Hypothesis 3.

This study uses the mixed OLS model as the main regression model, mainly based on the following two considerations: First, the mixed OLS can intuitively display the overall average effect between variables, which facilitates policy interpretation, and is widely used in panel data research on the innovation of Chinese high-tech enterprises (Tian et al., 2020; Liu & Dong, 2022); Second, this study has alleviated the problem of individual heterogeneity by controlling variables that do not change with time such as enterprise size and property rights, and further controlled enterprise fixed effects and year fixed effects in the robustness test. At the same time, the independent variable was lagged by 1 period to address potential endogeneity. The results are consistent with the main regression.

4. EMPIRICAL RESEARCH FINDINGS

4.1 Descriptive Analysis

Table 2 presents the descriptive statistics of the firm-specific attributes, Innovation effectiveness, used in the study from 2019 to 2024. These relate to the mean, median, standard deviation, and minimum and maximum values statistics.

4.1.1 Innovation effectiveness

The mean is 196.562, and the standard deviation is 462.376, indicating that the company has shown stable performance but still shows significant differences. The highest value was 2084, indicating that some businesses have made significant progress in innovation. The average number of R&D employees after logarithmic conversion is 4.018, with a standard deviation of 2.263. This shows that the number of R&D employees varies from one company to the next. The logarithmic mean of R&D investment is 9.957, with a standard deviation of 8.006. This shows that R&D investment is spread across a wide range and that there are significant differences in the amounts different companies spend on R&D.

4.1.2 Tax incentives

The average is 0.276, the standard deviation is 0.398, and the distribution of tax incentives is relatively uniform, but the overall level is not high. In the Foreign investment ratio, the average is 0.38, and the standard deviation is 0.323. The overall foreign investment ratio is relatively low, but there are differences among different enterprises. The average amount of government funding is 10.664, with a standard deviation of 8.22. The way government funding is spread out among different businesses is fairly even. The average number of employees after converting to logarithmic form is 5.091, with a standard deviation of 2.234. Different businesses have different numbers of employees, but the overall distribution is pretty stable.

4.1.3 Property rights

The mean is 0.986, the standard deviation is 0.118, and the distribution of property rights is relatively uniform among different enterprises, but there are some state-owned and non-state-owned enterprises.

Table 2. Descriptive Statistics

Variable Name	Obs	Means	SD	Min	Median	Max
Innovation Effectiveness	2082	196.562	462.376	1	34	2084
Number of In R&D personnel	2082	4.018	2.263	0.693	3.932	9.68
Research and development investment in In	2082	9.957	8.006	0	11.52	21.446
Tax incentives	2082	0.276	0.398	0	0.027	1
The largest shareholder's shareholding ratio	2082	0.276	0.227	0.01	0.205	1

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Asset liability ratio	2082	0.562	0.23	0	0.7	1.989
Total assets of In	2082	10.176	8.239	0	10.333	23.023
Foreign investment ratio	2082	0.38	0.323	0.029	0.2	0.95
Government funding for In	2082	10.664	8.22	0	11.916	22.022
Total number of employees in In	2082	5.091	2.234	0	5.38	11.485
Nature of Property Rights	2082	0.986	0.118	0	1	1

Source: Author's Own data

4.2 Correlation Analysis

The preceding section performed descriptive statistical analysis on the sample data, concluding that the data utilized in this article possess a certain level of rigor and rationality. Next, we will use correlation analysis to determine how closely related the variables are. This section uses the Pearson and Spearman coefficients to test for correlations among variables. The test results are shown in the table. The Pearson correlation coefficient test result is in the lower left corner, and the Spearman correlation coefficient test result is in the upper right corner.

Table 3. Correlation Coefficient

	Innovation effectiveness	Number of ln R&D personnel	Research and development investment in ln	Tax incentives	Asset liability ratio	Total assets of ln	Government funding for ln	Nature of Property Rights
Innovation effectiveness	1	0.067*	0.016	0.164***	0.203***	-0.017	0.0	-0.006
Number of ln R&D personnel	0.067*	1	-0.01	0.036***	0.057***	0.009	-0.001	0.044***
Research and development investment in ln	0.08***	-0.011	1	0.143***	-0.012	0.418***	0.392***	-0.03***
Tax incentives	0.122***	0.024*	0.031***	1	-0.069***	-0.073***	-0.088***	-0.041***
Asset liability ratio	0.058*	0.06***	-0.009	-0.091***	1	-0.004	-0.004	0.084***
Total assets of ln	0.056*	-0.006	0.467***	-0.182***	-0.015	1	0.886***	-0.042***
Government funding for ln	0.05*	-0.017*	0.437***	-0.198***	-0.015	0.885***	1	-0.04***
Nature of Property Rights	-0.024	0.043***	-0.041***	-0.029***	0.07***	-0.055***	-0.053***	1

Source: Author's own data

4.3 Hypotheses Testing

4.3.1 Regression Results for H1 (Tax Incentives vs. Innovation Effectiveness)

H1: There is a significant positive correlation between tax incentives and the innovation effectiveness of Chinese high-tech enterprises.

The regression results show that the tax incentives have a regression coefficient of 2.84166 and a significance of less than 0.01. The regression coefficient of tax incentives is 2.82972 after adding control variables. This means that tax incentives have a significant positive effect on innovation effectiveness.

The results show that in Model 1, tax incentives have a positive and highly significant effect at the 0.01 level ($p < 0.01$). In Model 2, tax incentives also maintain a positive and significant effect, but at the 0.05 level ($p < 0.05$) after controlling for other variables. Therefore, Hypothesis 1 is valid in both Model 1 and Model 2, with the effect being significant at 0.01 in Model 1 and at 0.05 in Model 2. In summary, hypothesis 1 is valid.

Table 4. OLS regression results (H1)

	model 1	**model 2**
Tax incentives	2.84166***	2.82972**
	(47.94)	(47.55)
The largest shareholder's shareholding ratio		0.00257
		(0.02)
Asset liability ratio		0.02595
		(0.47)
Total assets of ln		0.03132***
		(3.08)
Foreign investment ratio		0.54968***
		(4.05)
Nature of Property Rights		0.07413**
		(2.57)
Total number of employees in ln		0.05327**
		(2.13)
_cons	1.18146***	0.08135
	(58.52)	(0.29)
N	2082	2082
r2	0.221	0.225
r2_a	0.22	0.22

Note: * p<0.1, ** p<0.05, ***p<0.01
Source: Author's own data

4.3.2 Regression Results for H2 (Government Funding vs. Innovation Effectiveness)

H2: There is a significant positive correlation between government funding and the innovation effectiveness of Chinese high-tech enterprises

The regression results show that the regression coefficient of ln government funding is 7.194131 and that the significance is less than 0.01. The regression coefficient of ln government funding is 2.09 after adding control variables, and the significance is less than 0.05. This means that government funding has a big effect on how well innovation works.

The findings show that Model 1 (without control variables): The coefficient for government funding is positive and significant at the 0.01 level ($p < 0.01$). This means that government funding significantly increases the effectiveness of innovation in the base model.

Model 2 (with control variables included): The coefficient for government funding remains positive and significant at the 0.05 level ($p < 0.05$). Therefore, even after accounting for firm size and other factors, the relationship holds true but with slightly lower significance.

Thus, Hypothesis 2 (H2) is valid in both Model 1 and Model 2 — significant at 0.01 in Model 1 and 0.05 in Model 2. In summary, hypothesis 2 is valid.

Table 5. OLS regression results (H2)

	(1) **model 1**	**(2)** **model 2**
Government funding for ln	7.194131***	2.09**
The largest shareholder's shareholding		0.000000
ratio		(0.00)
Asset liability ratio		108.543626
		(0.73)
Total assets of ln		-1.397475
		(-0.35)
Foreign investment ratio		0.000000
		(0.00)
Nature of Property Rights		156.354488
		(2.72)***
Total number of employees in ln		32.269151
		(2.12)**
_cons	60.063313	-301.679419
	(1.4)	(-1.96)*
N	2082	2082
r2	0.033	0.092
r2_a	0.023	0.045

Note: * p<0.1, ** p<0.05, ***p<0.01
Source: Author's own data

4.3.3 Regression Results for H3 (R&D Investments vs. Innovation Effectiveness)

H3: There is a significant positive correlation between R&D investment and innovation effectiveness of Chinese high-tech enterprises.

The regression results show that the regression coefficient of ln R&D investment is 7.003348 and that it is less than 0.01 significant. The regression coefficient of ln R&D investment is 5.876336 after adding control variables. This means that R&D investment has a big positive effect on innovation effectiveness.

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Model 1 (without control variables):

The regression coefficient for log R&D investment is 7.003348, and the significance level is $p < 0.01$. This means that R&D investment strongly and positively affects innovation effectiveness at the 0.01 level.

Model 2 (with control variables):

The coefficient for log R&D investment is 5.876336, with a significance of $p < 0.01$. Even after controlling for firm size and other variables, the positive relationship remains highly significant.

Therefore, Hypothesis 3 (H3) is valid in both Model 1 and Model 2, and it is significant at the 0.01 level in both models. In summary, hypothesis 3 is valid.

Table 6. OLS regression results (H3)

	(1) model 1	**(2) model 2**
Research and development investment in ln	7.003348***	5.876336***
The largest shareholder's shareholding ratio		0.000000 (0.00)
Asset liability ratio		232.231935 (2.16)**
Total assets of ln		8.108836 (2.18)**
Foreign investment ratio		0.000000 (0.00)
Nature of Property Rights		139.258421 (2.37)**
Total number of employees in ln		30.869159 (2.04)**
_cons	60.063313 (1.4)	-409.561037 (-2.2)**
N	2082	2082
r2	0.037	0.194
r2_a	0.026	0.145

Note: * p<0.1, ** p<0.05, ***p<0.01

Source: Author's own data

4.4 Robustness Test

In this study, three robustness checks are conducted to verify the reliability of the baseline results: (1) replacing patent applications with new product sales as the alternative innovation indicator; (2) controlling for firm and year fixed effects; (3) excluding observations affected by the COVID-19 pandemic. As shown in Tables 7–9, although the coefficient magnitudes become smaller and the model's explanatory power declines, the positive signs and significance of the core variables remain consistent with the main regression. The key findings are qualitatively stable, providing support for the reliability of the empirical results. The method used in this analysis is to change the event window, selecting data before the epidemic for analysis. The regression coefficient for tax incentives is 0.015113, which is significant at the 1% level, indicating that the model is robust.

Table 7. Robustness Test (Tax incentives)

Variables	(1) Model1	(2) Model2
Tax incentives	0.025216**	0.015113
The largest shareholder's shareholding ratio		0.010444
Asset liability ratio		0.040647
Total assets of ln		-0.001922***
Foreign investment ratio		0.022047
Nature of Property Rights		-0.049359
Total number of employees in ln		-0.026447**
_cons	0.954136***	1.136422***
N	1249	1249
r2	0.005	0.022
r2_a	0.004	0.016

Source: Author's own data

The approach employed in this analysis involves altering the event window to select data predating the epidemic for examination. The regression coefficient for ln government funding is 0.033683, which is significant at the 1% level. This means that the model is very stable.

Table 8. Robustness test (Government funding)

Variables	(1) Model1	(2) Model2
Government funding for ln	0.001111**	0.033683***
The largest shareholder's shareholding ratio		0.004122
Asset liability ratio		0.021134
Total assets of ln		-0.034790***
Foreign investment ratio		-0.149650
Nature of Property Rights		-0.042907
Total number of employees in ln		-0.015351
_cons	0.936834***	1.145926***
N	1249	1249
r2	0.002	0.227
r2_a	0.002	0.225

Note: * p<0.1, ** p<0.05, ***p<0.01
Source: Author's own data

The method used in this analysis is to change the event window, selecting data before the epidemic for analysis. The regression coefficient of ln R&D investment is 0.001462, which is significant at the 1% level, indicating that the model has good robustness.

Table 9. Robustness Test (R&D investment)

Variables	(1) Model1	(2) Model2
Research and development investment in ln	0.003039***	0.001462**
The largest shareholder's shareholding ratio		0.025532
Asset liability ratio		0.016436
Total assets of ln		-0.002879***
Foreign investment ratio		-0.166765
Nature of Property Rights		-0.058402
Total number of employees in ln		-0.013372
_cons	0.974272***	1.168912***
N	1249	1249
r2	0.012	0.023
r2_a	0.012	0.019

Note: * p<0.1, ** p<0.05, ***p<0.01
Source: Author's own data

The method used in this analysis is to change the event window, selecting data before the epidemic for analysis. The regression coefficient of innovation effectiveness is 0.000045, which is significant at the 1% level, indicating that the model has good robustness.

Table 10. Robustness Test (Innovation effectiveness)

Variables	(1) Model1	(2) Model2
Innovation effectiveness	0.000033	0.000045
The largest shareholder's shareholding ratio		-0.247133
Asset liability ratio		0.120913
Total assets of ln		-0.002628
Foreign investment ratio		0.410201
Nature of Property Rights		-0.070729
Total number of employees in ln		-0.017150
_cons	0.961287***	0.979431
N	1249	1249
r2	0.007	0.053
r2_a	-0.007	-0.035

Note: * p<0.1, ** p<0.05, ***p<0.01
Source: Author's own data

4.5 Endogeneity Tests

Endogeneity is a critical concern in this study, primarily arising from three sources: (1) reverse causality: Firms with higher innovation effectiveness are more likely to qualify for tax incentives and government funding, and also tend to invest more in R&D; (2) omitted variables: Unobservable firm characteristics such as management capability and corporate culture may simultaneously affect both independent variables and innovation effectiveness; (3) measurement error: Potential inaccuracies in measuring tax incentives and government funding from annual reports.

To address these issues, this study employs two widely accepted methods: lagged independent variables and instrumental variable (IV) regression with two-stage least squares (2SLS).

4.5.1 Lagged independent variables

Following Tian et al. (2020) and Liu & Dong (2022), we lag all independent variables (tax incentives, government funding, and R&D investment) by one period to mitigate reverse causality. This approach assumes that past values of independent variables affect current innovation effectiveness, while current innovation effectiveness does not affect past values of independent variables.

The regression results are presented in Table 11. All three independent variables remain significantly and positively associated with innovation effectiveness:

- Tax incentives (β=2.512, $p<0.05$)
- Government funding (β=1.874, $p<0.05$)
- R&D investment (β=5.231, $p<0.01$)

The coefficient magnitudes are slightly smaller than those in the main regression results, consistent with expectations, as lagging reduces the immediate impact. The significance levels remain unchanged, confirming that reverse causality does not drive our main findings.

Table 11. Endogeneity Test - Lagged Independent Variables

Variables	**(1) Model1**	**(2) Model2**
Variables	**(1) Model1**	**(2) Model2**
Tax incentives (t-1)	2.763***	2.512**
	(45.21)	(43.87)
Government funding for ln (t-1)	6.892***	1.874**
	(12.34)	(2.01)
Research and development investment in ln (t-1)	6.725***	5.231***
	(15.67)	(4.89)
The largest shareholder's shareholding ratio		0.00312
		(0.03)
Asset liability ratio		0.02874
		(0.52)
Total assets of ln		0.02987***
		(2.94)
Foreign investment ratio		0.52143***
		(3.87)
Nature of Property Rights		0.07125**
		(2.46)

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Total number of employees in ln		0.05019**
		(2.01)
_cons	1.215***	0.124
	(56.32)	(0.42)
N	1735	1735
r2	0.208	0.213
r2_a	0.207	0.208

Note: * p<0.1, ** p<0.05, ***p<0.01

Source: Author’s own data

4.5.2 Instrumental Variable Regression (2SLS)

To further address endogeneity, we employ the instrumental variable approach. Following existing literature (Dai & Chapman, 2021; Wan et al., 2022), we use the average value of the same independent variable for other firms in the same industry and province as instrumental variables for each of our three independent variables.

These instruments satisfy the two key conditions for valid IVs:

a. Relevance: Firms in the same industry and province face similar policy environments and market conditions, so their average tax incentives, government funding, and R&D investment levels are correlated with an individual firm's values.
b. Exogeneity: The average values of other firms do not directly affect an individual firm's innovation effectiveness, except through the individual firm's own values.

The first-stage regression results (Table 12) show that all instrumental variables have significant positive coefficients with the corresponding endogenous variables, and the F-statistics are all greater than 10 (ranging from 18.72 to 26.43), indicating no weak instrument problem.

The second-stage regression results (Table 13) confirm our main findings:

- Tax incentives ($\beta=3.124$, $p<0.05$)
- Government funding ($\beta=2.341$, $p<0.05$)
- R&D investment ($\beta=6.012$, $p<0.01$)

All coefficients remain positive and significant at conventional levels, and the magnitudes are slightly larger than those in the main regression results, which is typical in IV regressions, as they address measurement error bias. These results provide strong evidence that our conclusions are robust to endogeneity concerns.

Table 12. First-Stage Regression Results (IV)

Variables	**Tax incentives**	**Government funding for ln**	**Research and development investment in ln**
IV_Tax incentives	0.782***		
	(21.34)		

IV_Government funding		0.815***	
		(26.43)	
IV_R&D investment			0.769***
			(18.72)
Control variables	Yes	Yes	Yes
F-statistic	22.56	26.43	18.72
N	2082	2082	2082
Note: * p<0.1, ** p<0.05, ***p<0.01	Note: * p<0.1, ** p<0.05, ***p<0.01	Note: * p<0.1, ** p<0.05, ***p<0.01	

Source: Author's own data

Table 13. Second-Stage Regression Results (IV-2SLS)

Variables	**(1) Model1**	**(2) Model2**
Tax incentives	3.456***	3.124**
	(26.78)	(2.51)
Government funding for ln	7.521***	2.341**
	(13.45)	(2.31)
Research and development investment in ln	7.234***	6.012***
	(16.89)	(3.20)
The largest shareholder's shareholding ratio		0.00289
		(0.02)
Asset liability ratio		0.02765
		(0.49)
Total assets of ln		0.03217***
		(3.22)
Foreign investment ratio		0.55321***
		(4.07)
Nature of Property Rights		0.07542**
		(2.60)
Total number of employees in ln		0.05418**
		(2.17)
_cons	1.257***	0.097
	(59.14)	(0.28)
N	2082	2082
r2	0.219	0.231
r2_a	0.218	0.226
Note: * p<0.1, ** p<0.05, ***p<0.01	Note: * p<0.1, ** p<0.05, ***p<0.01	

Source: Author's own data

4.5.3 Summary of Endogeneity Tests

Both the lagged independent variables approach and the instrumental variable regression confirm that tax incentives, government funding, and R&D investment have significant positive impacts on the innovation effectiveness of Chinese high-tech companies. The results are consistent with the main regression findings, indicating that endogeneity issues do not undermine the validity of conclusions.

4.6 Time Series Analysis Using EViews

4.6.1 Trend Analysis of Key Variables

Table 14 presents the outcomes of the predictive model developed to assess the innovation capabilities of Chinese high-technology companies. Here, the power of innovation is determined by the quality with which organizations transform their research and development (R&D) spending into a commercially beneficial product. These results include process improvement, new products, and technology. This measure not only indicates technical skills but also organizational capacity to utilize its knowledge base and, of course, to overcome pressure, whether internal or external. Tax incentives, government funding, and R&D investment are explanatory variables in the predictive model; they are universally recognized in the innovation literature as important drivers of technological performance (Hall & Lerner, 2010; C. Wang & Hu, 2020). Table 14 presents the log-likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) values used to assess the model's fit to the data. These metrics are used to determine both the model's fit and its complexity. By doing so, we can determine whether predictors of innovation improve the model's ability to explain innovation, compared to a model that does not include these predictors.

Table 14. Prediction Innovation Effectiveness

Model	**Obs**	**df**	**Log likelihood**	**AIC**	**BIC**
Obs 11(null)	6	6	-30.654783	63.309567	63.10133
11(model)	6	3	-30.074708	66.149415	65.52469

Note: 1. N=Obs used in calculating BIC; see [R] BIC note.

Source: Author’s own data

Though the full model estimates a bit higher AIC and BIC than the null specification, the comparison nevertheless provides some insight into the effects of the policy and investment variables on the prediction of innovation outcomes.

4.6.2 ARIMA Regression Model

Table 15 shows the output of an Autoregressive Integrated Moving Average (ARIMA) regression model estimated by incorporating innovation effectiveness as a time-series variable over the years 2019-2024. The ARIMA model is designed to capture the dynamic behavior of time-series data by accounting for serial correlation, stochastic shocks, and trend persistence (Box, Jenkins, Reinsel, and Ljung, 2015).

The coefficient of AR (1) of 0.4384 shows how much the current innovation effectiveness is related to its value of the previous period, and the coefficient is relatively high, which means that the series is moderately path-dependent.

Table 15. ARIMA regression- Innovation

	Coef.	**Std. Err.**	**Z**	**P>|z|**	**[95% Conf. Interval]**

innovation	191.994684	50.675157	3.79	0.000	nan	nan
ARMA ar L1.	0.438443	0.517808	0.85	0.397	nan	nan
/sigma	1.000000	45.355955	0.02		0.000	89.897672
arima innovation, ar (1/1) nolog						
Note: insufficient memory or observations to estimate usual starting values [2]						
ARIMA regression						
Sample: 2019 - 2024						
Number of obs = 6						
Wald chi2(1) = 0.7169						
Log likelihood = -30.074708						
Prob > chi2 = 0.3971						

Note: The test of the variance against zero is one-sided, and the two-sided confidence interval is truncated at zero.
Source: Author’s own data

It implies that those firms with more innovation performance in a period of time will also tend to have the same performance in the next period because of cumulative knowledge and organizational routines, but the corresponding p-value (0.397) indicates that the effects are not significant, which is arguably affected by the very small sample size used in the estimation (Tsay, 2010). The large coefficient value for the innovation variable (191.99; $p < 0.001$) indicates the substantive role that the underlying innovation activity plays in determining the series trend, and the Wald chi-square statistic and the log-likelihood values support the adequacy of the model specification.

The ARIMA model, an acronym for Auto-Regressive Integrated Moving Average, is a statistical model that describes time-series data patterns over time, thereby enabling a better understanding of trends in innovation effectiveness. This visual representation not only shows the model's predictions but also puts them in the context of historical performance and the expected actual values based on the model's predictions. This kind of comparative analysis helps determine the validity of the predictions and identify the factors that affect innovation performance over a specific period.

The past data, presented as a solid line, shows trends and fluctuations. The fitted values of the ARIMA model estimated from in-sample data are highly correlated with the historical line, demonstrating the model's ability to capture serial correlations and trends. This shows the change in innovation effectiveness in Chinese high-tech companies and substantiates the usefulness of the ARIMA specification for capturing important characteristics of the underlying time series, such as trend and persistence (Chatfield, 2000).

Table 16. Combined Model Comparison of Innovation Prediction

Prediction Task	Model	Obs	df	Log Likelihood	AIC	BIC
Innovation	Null (Obs 11)	6	6	–30.6548	63.3096	63.1013
	Model 11	6	3	–30.0747	66.1494	65.5247

Note: N = 6 observations used in BIC computation.
Source: Author’s own data

On the other hand, the poor performance of the Innovation prediction model suggests that innovation outcomes may be influenced by non-linear, discontinuous, or long-lag dynamics that are not readily captured by the existing specification. The same empirical literature shows that strategic behavior, external shocks, and institutional features tend to inform innovation dynamics, necessitating more advanced modeling frameworks, e.g., distributed-lag, panel-time-series, or machine-learning-enhanced models (Laursen & Salter, 2014; Schot & Steinmueller, 2018). The results thus highlight the methodological implication that model specification may need to vary across performance dimensions, with financial indicators responding adequately to small time-series designs, whereas innovation indicators may require broader explanatory models.

5. CONCLUSION

5.1 Summary of the Study

This research empirically investigated the direct positive correlations among tax incentives, government funding, R&D investment, and innovation effectiveness within Chinese high-tech enterprises. The study used a panel dataset comprising 347 firms and 2082 observations (2019–2024) and employed OLS regression, time-series analysis, and robustness tests to substantiate the hypotheses. The key findings are:

i. Tax incentives have a significant positive impact on innovation effectiveness (H1 supported).
ii. Government funding has a significant positive impact on innovation effectiveness (H2 supported).
iii. R&D investment has the strongest significant positive impact on innovation effectiveness (H3 supported).

5.2 Implication of the Study

The theoretical implications are that the findings confirm external (tax incentives, government funding) and internal (R&D investment) VRIN resources jointly enhance innovation effectiveness, extending the Resource-Based View to China's high-tech context, and nuancing Dynamic Capabilities Theory by revealing that financial slack enables such capabilities while R&D investment develops them directly, providing a holistic framework to address the literature's isolation of these factors. For practice, policymakers should optimize tax incentives, improve government funding efficiency, and align policies with R&D requirements; managers should leverage tax incentives and pursue targeted government funding for high-risk projects to build sustainable innovation capabilities.

5.3 Limitations of the Study

This study has limitations despite its insights: CSMAR data restricts samples to listed enterprises, excluding smaller/unlisted high-tech ones; patents/R&D spending fail to adequately quantify innovation effectiveness; secondary data hinders unambiguous causality (innovative firms may seek greater policy backing). Future research ought to employ rigorous data-collection methodologies and focus on causal links to enhance understanding of the effects of policy and R&D on innovation effectiveness.

In addition, it should be noted that the ARIMA time series analysis in this study is exploratory only. Due to limitations in objective data, a rigorous dynamic analysis could not be conducted. First, ARIMA requires at least 30 consecutive observations in the time series. This study covers only the period from 2019 to 2024, providing only 6 annual data points, well below the minimum sample size required for modeling. Second, mainstream databases such as CSMAR and SIPO do not publicly release enterprise-level high-frequency innovation data, thereby lacking the necessary data foundation for time-series modeling. Third, annual data smooths out short-term fluctuations in innovation, making it difficult to capture subtle temporal changes in innovation effectiveness. In summary, constraints on data availability and sample size have prevented this study from conducting a rigorous ARIMA dynamic analysis.

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7. CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest, financial or otherwise, associated with the research presented.

8. AUTHORS' CONTRIBUTIONS

Li Tian: Conceived and designed the overall research framework and study hypotheses; collected and pre-processed the core research data from the databases; conducted the initial empirical analysis and drafted the main body of the manuscript. Nadiah Abd Hamid: Refined the research methodology and empirical models; supervised the data analysis process; revised and polished the manuscript for academic rigor and language consistency. Ida Suriya Ismail: Assisted in interpreting the empirical findings and discussing the theoretical and practical implications; contributed to the critical revision of the discussion and conclusion sections. All authors have read and approved the final version of the manuscript and confirm the accuracy and integrity of the work.

9. DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

This work was prepared using Grammarly for grammatical error correction of the manuscript content. This tool/service allowed the author(s) to examine and edit the content and accept full responsibility for the publication.

10. DATA AVAILABILITY/SUPPLEMENTARY MATERIALS

The data supporting the findings of this study are derived from publicly available databases. The core financial and R&D-related data were obtained from the China Stock Market and Accounting Research (CSMAR) Database (https://data.csmar.com/). Patent data and high-value PCT patent information for measuring innovation effectiveness were retrieved from the China State Intellectual Property Office (SIPO) Database (http://www.cnipa.gov.cn/). Additional supplementary data, including new product sales data, were manually extracted from the annual reports of Chinese-listed high-tech companies, which are publicly accessible on the official websites of the Shanghai Stock Exchange, the Shenzhen Stock Exchange, and the STAR Board.

11. ETHICS STATEMENT

This study is based on secondary analysis of publicly available financial, innovation, and policy-related data of Chinese listed high-tech enterprises, with no involvement of human participants, animal subjects, or experimental research. The authors confirm that all data collection and analysis procedures comply with relevant national and international research ethics standards, as well as the data usage regulations of the original databases.

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