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The Impact of Scientific Research Level on Financing for High-tech Enterprises in China: Machine Learning Analysis Based on the STAR Market

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Abstract: Amid the prevailing trend of technological supremacy, the scientific research level plays a pivotal role in elevating economic growth and national comprehensive strength. As crucial forces propelling industrial advancement and economic expansion, high-tech companies share an intricate relationship between scientific research level and enterprise strengths. This study delves into the influence of research level on the financing capacity of enterprises in the STAR market. It employs Ordinary Least Squares (OLS) regression and Gradient Boosting Regression Trees (GBRT) techniques to analyze data between 2019 and 2022. The findings underscore that patent research capabilities and research investment intensity are key factors impacting financing capacity. Specifically, patent quantity exhibits a negative correlation with Asset-liability ratio (ALR), while research investment intensity shows a positive correlation. On the other hand, patent quantity correlates positively with commercial credit financing (CCF) capacity, whereas the proportion of research personnel correlates negatively. The GBRT analysis further validates the significant impact which patent quantity and research investment have on financing capacity. This suggests that high-tech companies should focus on enhancing research efficiency and the proportion of research personnel, while also carefully considering the degree of emphasis on innovation. These measures can balance CCF and debt ratio considerations. The study provides essential decision-making insights for managers and investors of technology-driven firms, emphasizing the significance of technological innovation in business development. Also, it offers guidance for optimizing corporate development and personnel structures in the technology and innovation sectors.

Keywords: finance, GBRT, star market

1. Introduction

In today's era of technological advancement and globalization, the innovation and industrialization of advanced technologies have a significant impact on a country's overall strength. Innovation capabilities directly enhance the competitiveness of both companies and countries on a global scale, driving economic progress and growth. Technology-oriented companies are dedicated to translating laboratory technologies into practical applications, playing a crucial role in promoting technological innovation and development in our country [1]. Therefore, in this technology-driven environment, high-tech companies have become a crucial force in driving the upgrading of national industrial structures and promoting economic development. They represent the primary source of national technological innovation [2]. The success of these high-tech companies is closely linked to their research and development (R&D) capabilities. R&D capabilities often represent the ability and output of researchers, the intensity of a company's R&D investment, and the degree of achievements in technology commercialization. High-Tech employees, as the core driving force behind a company's innovation, play a vital role in determining its performance. One of the many impacts of a company's R&D capabilities is its financing ability. This represents the magnitude of funding a company can obtain through financing. For high-tech enterprises, financing capability is closely related to the company's potential to create greater value and make more technological innovations. The strength of financing ability also influences the decisions of managers and investors.

In recent years, the application of statistical learning and machine learning methods in the financial domain has become increasingly widespread, providing financial institutions with new tools to tackle complex problems. The volatility and uncertainty of financial markets pose significant challenges to risk management. Statistical learning methods can assist financial institutions in better assessing and managing risks by analyzing historical data and constructing predictive models. For example, investors and financial companies can build risk models for measuring and diversifying investment portfolios, thereby improving investment returns and safety.

The combination of statistical learning and machine learning has become a hot topic in the current financial technology field. With financial markets becoming increasingly complex, financial data has grown exponentially. As a result, traditional statistical methods have struggled to meet the demands of data analysis. However, machine learning, as a powerful data-driven approach, excels in handling large-scale data, identifying complex patterns, and adapting rapidly. It has gradually shown unique application value in the financial domain [3]. Machine learning and artificial intelligence (AI) technologies can bring significant advantages to financial decision-makers by utilizing efficient modeling and prediction methods. In recent years, the financial industry has recognized this potential, with a projected global annual investment of approximately 28 billion USD in AI technologies by 2021[4]. Machine learning can aid financial institutions in predicting risks more accurately, optimizing asset allocation, and identifying potential trading opportunities in the market. These algorithms can handle not only structured data, such as historical transaction data and financial statements, but also unstructured data, such as social media sentiment and news events, to provide more comprehensive information for risk decision-making [5].

In previous studies, research capability and factors affecting enterprise financing capacity have been explored. However, research on the relationship between research capability and financing capacity in the field of science and innovation remains relatively scarce. In a study conducted by Lu on companies applying for listing on the Star Market between 2019 and 2020, machine learning techniques were employed to reveal that R&D capability, growth potential, and corporate governance significantly influence a firm's future development. Notably, R&D capability was found to be the most critical factor determining a company's potential for going public [3]. Another study by Sun et al. used AHP and fuzzy comprehensive evaluation methods to construct a quantitative model for assessing the financing capacity of technology-oriented small and medium-sized enterprises (SMEs). The model encompassed four categories of indicators: technological ability, guarantee capacity, financial capacity, and environmental factors [6]. Chen et al. analyzed the factors influencing the financing capacity of SMEs listed on the SME board. Their findings indicated positive correlations between enterprise size, asset turnover efficiency, asset collateral value, and financing capacity. On the other hand, profitability, risk resistance capacity, and growth potential were negatively related to financing capacity [7].

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Most SMEs in China prefer debt financing when choosing financing methods, so the debt level can well reflect the financing situation of the enterprise. The debt financing capacity can be measured using ALR. Huang utilized ALR as the dependent variable and employed a fixed-effects model on panel data from 83 technology-oriented SMEs listed companies between 2019 and 2021. The empirical analysis demonstrated that enterprise size, guarantee capacity, and fund turnover efficiency had a significant positive impact on the financing capacity of technology-oriented SMEs [8]. Furthermore, CCF, as an informal financing channel, played a vital role in supporting the production and operations of enterprises, and thus, it was commonly used to assess the financing situation of companies. Li et al. researched the impact of digital transformation on CCF using data from Chinese A-share listed companies between 2011 and 2020. Their study revealed that digital transformation facilitated companies in obtaining more CCF [9].

Given the known influence of research capability and technological ability on enterprise financing, this study proposes several hypotheses regarding the significance of innovation capability and research investment on financing capacity in science and innovation companies. The goal is to deeply investigate the correlation between scientific research level and financing capacity using statistical learning and machine learning methods. This study aims to unveil the mechanisms by which innovation capability and research investment influence a company's financing capacity. Then this study can provide reliable decision-making support and strategic guidance for science and innovation company managers, stock market regulators, and investors. By understanding the impact of research capability on financing capacity, company managers can design their workforce structure more scientifically, enhance the company's innovation ability, and improve the ratio of research output to investment, leading to better company performance. Similarly, stock market investors can make rational investment decisions based on relevant indicators such as a company's research and development performance.

2. Methods

This study employs both OLS regression and GBRT to conduct data analysis. Initially, the OLS method is used to fit the dependent variable with explanatory variables and control variables, thereby selecting the significant explanatory variables related to the dependent variable. Subsequently, the GBRT are utilized to investigate the importance of different explanatory variables in predicting the dependent variable, leading to the ranking of their relative importance.

GBRT effectively combines decision trees and ensemble techniques from machine learning, enhancing the fitting performance by weighting multiple base regression trees. This approach achieves high levels of fitting accuracy both within and outside the sample. During the training process, this study adopts a 5-fold cross-validation technique to determine the optimal number of base regression trees. The selected regression tree is then used to generate the output of the relative importance scores for the explanatory variables. The research utilizes the ‘summary’ function to examine the relative importance scores of each independent variable, where higher scores indicate greater contributions of the variable to predicting the dependent variable [10].

2.1. Response Variables

The financing capability of a company is commonly measured using two indicators: CCF and Total Debt Ratio (ALR). Thus, this study constructs two models, referred to as the CCF model and the ALR model, with CCF or ALR as the dependent variables. Generally, a higher ALR implies a lower financing capability for the company. Therefore, researchers often use ALR to assess a company's financing capability, which is calculated as the total liabilities divided by the total assets.

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In contrast to ALR, a higher value of CCF indicates that the company is favored with more capital, usually signifying a stronger financing capability. According to Ying, CCF has a significant positive impact on the company's growth, especially in promoting private enterprises. Ying and other researchers commonly measure the CCF indicator as (Accounts Payable + Notes Payable + Advance receipts) / Total Assets [11].

2.2. Predictors

The explanatory variables for a company's scientific and research level are derived from its innovative capability and the investment intensity of R&D. In this study, the innovative capability is assessed using Patent R&D Capacity and Efficiency, which is determined by factors respectively: the number of patents obtained annually (Patents) and the number of patents per thousand people (Patentsperthoud) [3]. The total number of patents obtained is the sum of three types of patents: Invention Patents (Invention), Utility Model Patents (UtilityModel), and Design Patents (Design) [1]. The study is divided into the Total Patent Model and the Sub-item Patent Model, with the independent variables being Patents and the three individual types of patents.

Table 1: Variables description.

Type	Variables	Name	
Response Variables	CCF	Commercial credit financing	(Notes payable + Accounts payable + Advance receipts) / Total assets
	ALR	Asset-liability ratio	Total Liabilities / Total Assets
Predictors	RDSpendSumR	Ratio of R&D investment to operating income	
	RDPersonR	Proportion of R&D personnel	Number of R&D personnel / Total number of employees
	Invention	Invention patents	
	UtilityModel	utility model patents	
	Design	design patents	
	Patents	Number of patents obtained	
	Pantensperthoud	Number of invention patents per thousand people	Number of patents * 1000 / Number of R&D personnel
Control Variables	CurrentR	Current ratio	Current assets / Current liability
	CollateralV	Collateral Value of Assets	(Inventory + Fixed assets) / Total assets
	TurnoverR	Asset turnover rate	Main operating income / Total assets
	RetentR	Retained earnings ratio	Undistributed profits / Total assets

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Furthermore, the investment intensity of R&D is measured by two ratios: R&D investment ratio (RDSpendSumR) and R&D personnel ratio (RDPersonR) [6, 12]. The R&D investment ratio represents the proportion of R&D investment to total operating income, while the R&D personnel ratio indicates the proportion of R&D personnel to the total number of employees. In conjunction with existing research on company financing capability, this study incorporates several control variables: current ratio (CurrentR), collateral value of assets (CollateralV), asset turnover rate (TurnoverR), and retained earnings ratio (RetentR) [7, 8]. The specific measurement methods for each control variable are outlined in Table 1.

In the linear regression models, both the CCF model and the ALR model are constructed based on different sets of independent variables, leading to the creation of two types of models: the Total Patent Model and the Sub-item Patent Model. The Total Patent Model uses the independent variable ‘Patents’, while the Sub-item Patent Model employs three individual independent variables: ‘Invention’, UtilityModel’, and ‘Design’. Additionally, the other explanatory variables remain unchanged. After performing the linear regression, the model with better fitting performance will be selected for further analysis using Gradient Boosting Tree Regression to explore the data.

2.3. Data and Samples

This study focuses on A-share companies listed on the Chinese Sci-Tech Innovation Board (STAR Market) from 2019 to 2022 as the research subjects. The necessary data for the empirical analysis are sourced from the China Securities Market & Accounting Research (CSMAR) database.

During the empirical analysis, the data underwent several processing steps: Firstly, companies categorized as "ST" (indicating a risk of delisting) were excluded due to their unstable business operations [13, 14]. Secondly, companies that did not obtain any patents for three consecutive years from 2019 to 2022 were also excluded. Additionally, companies with missing records for explanatory variables were removed from the analysis. For instances where a company obtained patents but specific types of patents were not recorded, the count for those specific patent types was imputed as zero. After applying these data processing steps, a total of 382 companies with 1144 valid samples were obtained for further analysis.

Python and R programming languages were employed for data processing in this research.

3. Results and Discussion

3.1. Descriptive Statistics

Table 2 below presents the final descriptive statistics of the dataset. From the descriptive statistical analysis of the variables, it was observed that the standard deviation of the number of patents is relatively large, indicating significant variations in patent research and development among different companies. Additionally, there is a substantial gap between the maximum value and the 75th percentile, suggesting the possibility of some companies being industry leaders, obtaining a significantly higher number of patents than the average.

After manually reviewing the data, it was found that the maximum values for all types of patents are attributed to the company ‘CICT Mobile Communication Technology Stock’ (a pseudonym), and the number of its patents is more than twice the number obtained by the second-highest company. As a result, the data for ‘CICT Mobile Communication Technology Stock’ is considered an outlier and has been removed from the analysis.

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Table 2: Descriptive statistics of data.

variable	count	min	max	mean	std
CCF	1144	0.00014	0.7699	0.1035	0.0919
ALR	1144	0.0156	1.0885	0.2574	0.2574
Patents	1144	1	937	50.4956	90.9750
Invention	1144	0	672	19.2220	45.4642
UtilityModel	1144	0	627	25.5061	53.0016
Design	1144	0	282	5.4650	19.6436
RDSpendSumR	1144	1.55	31728.84	71.0281	1092.1377
RDPersonR	1144	0.2078	90.42	29.9605	18.2532
Patentsperthoud	1144	0.9447	2218.75	184.8714	196.8048
CurrentR	1144	0.5760	66.6107	6.0280	6.0836
CollateralV	1144	0.0032	0.6847	0.2311	0.1320
TurnoverR	1144	0.0002	1.9518	0.4218	0.2491
RetentR	1144	-7.6729	0.7468	0.1312	0.3015

3.2. Results of Linear Regression Model

3.2.1. ALR Model

Table 2 presents the descriptive statistical results of the final dataset. Upon observing the data, notable differences in magnitudes exist among the various variables, with values reaching up to the order of cubic power of 10. To address this difference, the data were subjected to standardization before conducting linear regression analysis.

The outcomes of the linear regression models are displayed in Tables 3 and 4. In ALR model with Sub-item Patent Model and Total Patent Model, the p-values for the majority of explanatory variables have passed the significance tests. However, the variables of ‘Invention’ and ‘RDSpendSumR’ failed to achieve statistical significance. This outcome suggests that these two variables are not substantially related to ALR. One plausible explanation could be the extended review period for invention patents, making their direct impact on a company's assets less straightforward. Compared to research investment, the relationship between ALR and research output is more closely intertwined.

Regarding the significance findings, the relationships between UtilityModel, RDPersonR, Patentsperthoud, CurrentR, CollateralV, TurnoverR, RetentR, and the dependent variable are highly significant at the 0.001 level, with Design showing significance at the 0.01 level. Analyzing the regression coefficients reveals that Design, RDPersonR and Patentsperthoud exhibit negative coefficients, indicating a negative correlation with the ALR. Conversely, the regression coefficients for Patents and UtilityModel are positive, suggesting that a higher number of patents leads to an increase in the ALR. This phenomenon is likely due to the ongoing financial investment required for patent development and acquisition, potentially augmenting both loan amounts and liabilities.

In summary, this research underscores the substantial impact of patent research capabilities and R&D investment intensity on the ALR, which is indicative of a company's financing capacity. Higher R&D investment intensity corresponds to a weaker ALR. Conversely, the influence of patent quantity on the asset-liability ratio follows the opposite pattern.

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Table 3: ALR model with Sub-item Patent Model.

Variables	-	Estimate value	P-value	Significant level
ALR	Y			
Intercept	α	0.0000		
Invention	X_1	0.0301	0.156	
UtilityModel	X_2	0.2140	<0.001	***
Design	X_3	-0.0740	0.001	**
RDSpendSumR	X_4	-0.0025	0.899	
RDPersonR	X_5	-0.0838	<0.001	***
Patentsperthoud	X_6	-0.0930	<0.001	***
CurrentR	X_7	-0.4499	<0.001	***
CollateralV	X_8	0.1409	<0.001	***
TurnoverR	X_9	0.1843	<0.001	***
RetentR	X_{10}	-0.2599	<0.001	***

Table 4: ALR model with Total Patent Model.

Variables	-	Estimate value	P-value	Significant level
ALR	Y			
Intercept	α	0.0000		
Patents	X_1	0.1570	<0.001	***
RDSpendSumR	X_2	-0.0025	0.902	
RDPersonR	X_3	-0.1025	<0.001	***
Patentsperthoud	X_4	-0.0833	<0.001	***
CurrentR	X_5	-0.4475	<0.001	***
CollateralV	X_6	0.1557	<0.001	***
TurnoverR	X_7	0.1774	<0.001	***
RetentR	X_8	-0.2605	<0.001	***

3.2.2. CCF Model

The linear regression outcomes of CCF model are displayed in Tables 5 and 6. In the CCF model, there has been a reduction in the number of variables that pass the p-value test: Patents, RDSpendSumR, Patentsperthoud, and CollateralV did not meet the significance criteria. These variables do not exhibit a clear relationship with CCF. The significance results reveal that Patents and UtilityModel are highly significant, while the RDPersonR achieves significance at the 0.001 level and Design holds significance at the 0.01 level.

Examining the regression coefficients of Sub-item Patent Model and Total Patent Model, it is evident that the coefficients for Design and RDPersonR are negative. This signifies a negative correlation between these variables and CCF. Conversely, the regression coefficients for Patents and UtilityModel are positive, indicating a positive correlation with CCF capability.

The overall outcomes suggest that a higher number of patents is associated with stronger CCF capability for enterprises, while a higher ratio of R&D personnel is associated with weaker CCF performance. This relation can be attributed to the rapid conversion of obtained patents into company benefits, thereby enhancing investor confidence and subsequently increasing the prospects for CCF. Concurrently, the elevated proportion of R&D personnel reflects the company's focus on research and development rather than sales. This emphasis might lead investors to harbor concerns about investment returns, thus potentially influencing the company's financing capacity.

Table 5: CCF model with Sub-item Patent Model.

Variables	-	Estimate value	P-value	Significant level
CCF	Y			
Intercept	α	0.0000		
Invention	X_1	-0.0274	0.262	
UtilityModel	X_2	0.2519	<0.001	***
Design	X_3	-0.0637	0.015	*
RDSpendSumR	X_4	0.0077	0.736	
RDPersonR	X_5	-0.0821	0.002	**
Patentsperthoud	X_6	-0.0346	0.171	
CurrentR	X_7	-0.3156	<0.001	***
CollateralV	X_8	0.0441	0.097	.
TurnoverR	X_9	0.2860	<0.001	***
RetentR	X_{10}	-0.2337	<0.001	***

Table 6: CCF model with Total Patent Model.

Variables	-	Estimate value	P-value	Significant level
CCF	Y			
Intercept	α	0.0000		
Patents	X_1	0.1488	<0.001	***
RDSpendSumR	X_2	0.0078	0.736	
RDPersonR	X_3	-0.1056	<0.001	***
Patentsperthoud	X_4	-0.0169	0.507	
CurrentR	X_5	-0.3123	<0.001	***
CollateralV	X_6	0.0607	0.024	*
TurnoverR	X_7	0.2868	<0.001	***
RetentR	X_8	-0.2328	<0.001	***

3.2.3. GBRT Model

The linear regression results reveal that the ALR model has a larger R square value and more significant independent variables. Therefore, the study selects the ALR as the dependent variable and employs GBRT to conduct further analysis, as shown in Table 7.

For the Sub-item Patent Model, the 5-fold cross-validation method identifies the optimal number of iterations for the regression tree as 85, and the relative importance scores are generated using this regression tree model. In descending order of importance for ALR, the variables are as follows: UtilityModel, RDPersonR, Invention, Patentsperthoud, and Design. It is worth noting that the relative importance of design patents is negligible and can be disregarded. The relative importance of the other two types of patents ranks first and third, indicating that the number of patents has a significant impact on ALR.

For the Total Patent Model, the optimal number of iterations is 82 by 5-fold cross-validation, and the relative importance rankings of the independent variables are as follows: Patents, RDPersonR, and Patentsperthoud. The relative importance of the total number of patents exceeds that of patents per thousand people for patents by more than twice, indicating significant differences between the variables.

Combining the results from both models, it is evident that the absolute number of patents has the most significant impact on the dependent variable. The influence of the proportion of R&D personnel and patents per thousand people for patents is slightly less, but they show a similar magnitude of

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impact. The results indicate that the asset-liability ratio places more importance on the absolute quantity of research and development results, while the efficiency or input of R&D personnel has a less pronounced effect on ALR.

Table 7: The relative importance scores of ALR model (Left: Sub-item Patent Model; Right: Total Patent Model).

Variables	significant	Variables	significant
UtilityModel	28.9722	Patents	43.9440
RDPersonR	27.7917	RDPersonR	35.0804
Ivention	22.9552	Patentsperthoud	20.9757
Patentsperthoud	20.0366	-	-
Design	0.2462	-	-

4. Conclusion

This study delves into the impact of scientific and research capability on the financing capacity of high-tech enterprises, utilizing both linear regression and GBRT models for empirical research. The findings reveal that a higher number of patents and a lower proportion of R&D personnel are associated with stronger CCF capability for these innovative enterprises.

Regarding the asset-liability ratio, both patent research capability and R&D investment intensity significantly influence it. Higher R&D investment intensity is linked to a lower asset-liability ratio, while a higher number of patents has the opposite effect. The results from GBRT suggest that the ALR places more emphasis on the absolute quantity of patent achievements, with R&D efficiency or personnel input having a slightly less pronounced impact on ALR but still exerting a significant influence.

In summary, increasing the proportion of R&D personnel and improving patent research efficiency contribute to reducing the asset-liability ratio for technology-driven innovative enterprises. However, an increased proportion of R&D personnel may simultaneously lower the CCF capability. Additionally, having more patents and technological innovations can attract more support in CCF, further promoting innovation and development within the company, but it can also elevate the asset-liability ratio. Balancing CCF and the asset-liability ratio could become a crucial development decision for technology-driven innovative enterprises in the future.

The research results further emphasize the importance of technological innovation for corporate development and economic progress. Technology-driven innovative companies should consistently value their employees' innovation capabilities and patent output efficiency while considering the trade-offs between CCF and the asset-liability ratio. To enhance innovation capabilities, companies should actively incentivize their employees to engage in scientific innovation, possibly through reward systems to improve the efficiency of R&D personnel. Simultaneously, optimizing the personnel structure by increasing the proportion of R&D personnel and enhancing R&D patent efficiency can help lower the asset-liability ratio. However, companies should also be mindful of the extent of R&D investment and personnel adjustments to secure more opportunities for CCF. These findings provide critical decision-making support and strategic guidance for the managers and investors of high-tech companies.

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