

Impact of technological innovation on the performance of Chinese listed seed companies: The moderating role of supply chain concentration

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Abstract: This study examines the impact of technological innovation on the performance of Chinese seed firms, as well as the moderating effect of supply chain concentration, aiming to provide actionable strategies for seed firms to enhance their sustainable development. Analyzing panel data from Chinese listed seed firms (2013–2022) through lagged regression models, results show that both R&D intensity and patents have a significant negative impact on ROE in the current period, likely due to short-term cost pressures. However, R&D intensity exhibits a significant positive relationship with ROE from a lag of two periods, indicating long-term benefits. Patents show a positive but insignificant relationship from a lag of three periods. Supply chain concentration weakens the negative relationship between R&D intensity and ROE, suggesting that optimizing supply chain concentration can moderate short-term costs and enhance long-term performance. Given the unique industry characteristics of seed companies, strategic supply chain management is crucial for leveraging innovation investments. This study highlights the importance of balancing short-term costs with long-term benefits in driving sustainable competitiveness.

Keywords: Chinese seed industry, Firm performance, Moderating effect, Technological innovation.

1. Introduction

The seed industry is crucial for the sustainable development of the global food supply chain. Seed, as the starting point of the agricultural industry chain, is one of the most important inputs in agricultural industry [1, 2]. According to the UN [3] state of Food Security and Nutrition in the World Report, the number of hungry people has been growing since 2014, which means that more than 840 million people would suffer lack of food in 2030. However, few studies focus on the seed industry and seed companies. China has had very few food security problems for many years [4] which is mostly due to the supportive of technological innovation in the seed industry in China [5]. Seed industry technological innovation strategy has been lasting for more than 10 years. Research has shown that technological innovation significantly enhances firm performance [6] but this relationship is underexplored in the seed industry. Supply chain concentration reflects the extent to which a firm relies on key suppliers and customers, which is particularly critical in the agricultural sector. A highly concentrated supply chain may enhance the efficiency of technology transfer through close collaboration [7] but it can also suppress innovation returns due to imbalanced bargaining power [8]. This contradictory nature makes supply chain concentration an important moderator in the relationship between technological innovation and performance. Therefore, the objective of this paper is to analyze the impact of technological innovation on firm performance in Chinese seed industry with a moderator of supply chain concentration. It would help the seeds companies to formulate a more scientific and reasonable technological innovation strategy, better carry out R&D activities and improve firm performance.

In 2013, the Office of the State Council issued the "Opinions on Deepening the Reform of the Seed Industry System and Improving Innovation Capability" (referred to as "Article 7"). This document highlighted the role of seed companies as key market players in technological innovation for the first time in China's seed industry history. Consequently, this study selects 2013 as the starting point and examines the performance of Chinese seed companies over a 10-year period from 2013 to 2022. The study sample comprises 34 publicly listed crop seed companies in China, and their financial data from 2013 to 2022 are analyzed to assess the impact of technological innovation on firm performance, with supply chain concentration serving as a moderator factor.

The study is organized as follows: Section 2 presents the literature review and hypothesis development. Section 3 outlines the study methodology, variables, and data description. Section 4 discusses the study results. Finally, Section 5 provides the conclusion of the study.

2. Literature Review and Hypothesis

2.1. Technological Innovation (TI) and Firm Performance (FP)

Technological innovation capabilities that are unique, replicable, and non-substitutable give businesses a competitive advantage and improve their market performance in line with the firm's return on value [9]. According to the resource-based view (RBV) theory, a company's technological innovation capability is believed to enhance performance value through the effective development, organization, and coordination of its resources and capabilities [10-12]. Furthermore, technological is recognized as a crucial factor in driving business success by generating value [13]. Seed industry companies have achieved initial accumulation of technological levels through continuous accumulation. After a certain level of accumulation, the company's innovation capabilities may not be improved. However, the potential technological level of the company increases significantly. Through the improvement of these capabilities, the company continues to improve the potential technical level and complete the company's technology accumulation [14]. Sufficient research and development investment can provide companies with abundant germplasm resources, high-quality scientific research teams and advanced breeding technology and equipment to ensure the continuity of excellent varieties of companies, accelerate the research and development of new varieties that meet market demand, and obtain huge market, and finally complete the Company's Company performance. Regarding the design of measurement indicators for technological innovation, most studies are measured from the perspectives of input and output. The input indicators for technological innovation mainly include R&D investment [15-17]. The output of technological innovation mainly includes indicators such as the number of patents [15]. Thus, the following hypotheses are proposed:

H^1 : *Technological innovation (TI) has significant impact on Chinese seed firm performance (FP)*

H^{1a} : *RD investment (RD) has significant impact on Chinese seed firm performance (FP).*

H^{1b} : *Patent (PA) has significant impact on Chinese seed firm performance (FP).*

2.2. Technological Innovation (TI), Supply Chain Concentration (SCC) and Firm Performance (FP)

Supply Chain Concentration (SCC), comprising supplier and customer concentration, plays a dual role in firm performance. While high SCC may reduce collaboration costs through relationship cohesion, it also increases dependency risks Kim and Henderson [18] and Zhang [17]. Wei, et al. [19] investigates the complex relationship between supply chain concentration (reliance on key suppliers and customers) and firm financial performance in China. Utilizing resource dependence theory (RDT) and transaction cost theory (TCT), the authors find a U-shaped relationship between both supplier and customer concentration and firm performance, suggesting that moderate concentration is optimal. Furthermore, the study explores the moderating roles of marketing and operational capabilities, demonstrating that strong marketing capability enhances the positive effects of supplier concentration, while strong operational capability mitigates the negative effects of high customer concentration [19]. The findings offer valuable insights for managers to optimize supply chain strategies and improve financial performance. Chen, et al. [20] investigates the effects of supply chain concentration (SCC) on

supply chain integration (SCI) and subsequent business performance, considering the moderating role of environmental turbulence. Chen, et al. [20] empirically examine whether concentrating business with a few key suppliers or customers enhances integration and profitability. Their findings reveal a positive relationship between customer concentration and customer integration, but a non-significant effect for supplier concentration and supplier integration. Importantly, market turbulence weakens the link between concentration and integration, while technological turbulence strengthens it Chen, et al. [20]. Ultimately, the study provides a nuanced understanding of how supply chain concentration strategies should be tailored to specific environmental conditions to optimize business outcomes.

From a relational perspective, trust is a critical mechanism through which SCC influences performance. Trust reduces transaction costs and enhances knowledge transfer, fostering co-innovation with stakeholders. Conversely, low trust may lead to overlooked external innovations and performance decline. Given that close supply chain relationships (reflected by high SCC) are often built on long-term trust [8] this study uses SCC as a proxy for inter-firm trust. Thus, the following hypothesis is proposed:

H2: Supply Chain Concentration (SCC) moderates between technological innovation and Chinese seed firm performance (FP).

Based on the literature review and hypotheses, the research framework is described in the following figure.

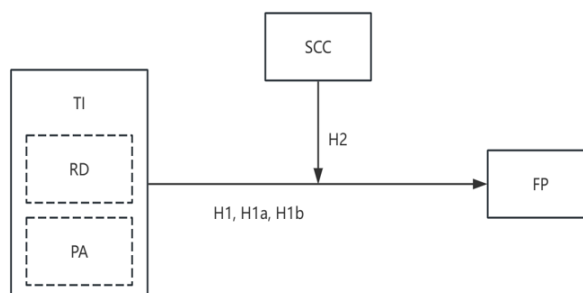


Figure 1.
Research Framework

3. Methodology

3.1. Model Specification

The purpose of this model is to examine the impact of technological innovation on performance of Chinese seed firms.

$$FP_{it} = \alpha + \beta_1 RD_{it} + \beta_2 PA_{it} + \sum \beta_k Controls_{it} + u_{it} \quad (1)$$

$$FP_{it} = \alpha + \beta_1 RD_{it} + \sum \beta_k Controls_{it} + u_{it} \quad (1a)$$

$$FP_{it} = \alpha + \beta_2 PA_{it} + \sum \beta_k Controls_{it} + u_{it} \quad (1b)$$

The purpose of this model is to test Supply Chain Concentration ratio (SCC) as a moderator impact technological innovation (TI) on performance of Chinese seed firms.

$$FP_{it} = \alpha + \beta_1 RD_{it} + \beta_2 PA_{it} + \beta_3 SCC_{it} + \beta_4 SCC_{it} * RD_{it} + \beta_5 SCC_{it} * PA_{it} + \sum \beta_k Controls_{it} + u_{it} \quad (2)$$

In above models, i represents individual seed firm, t represents year. FP represent Chinese seed firm performance, TI represents technological innovation, RD represent R&D investment, PA represents patent, and SCC represents supply chain concentration u_{it} indicate the fixed effect of firm, the fixed effect of year and the error respectively.

3.2. Variables

Dependent Variable (DV). Firm Performance (FP) is the dependent variable of this study. ROE (Return on Equity) and ROA (Return on Assets) are a common measure of firm performance [15, 21,

22] reflecting both profitability and growth. Referring to related research [23] this study selects return on equity (ROE) to measure firm profitability. ROA is used to test robustness. All the indicators' calculation formulas are based on Chinese accounting regulation, and the result of the calculation can be found on CSMAR (China Stock Market & Accounting Research) database.

Independent variable (IV). Technological innovation (TI) is independent variable of this study. Technological innovation (TI) is expressed by two indicators in this study, which are R&D intensity [15, 24] and patents [15, 25].

Moderator variable (MV). Supply Chain Concentration (SCC) would be the moderator of this study. Referring to the method by scholars [7, 8, 26] SCC would be measuring by the average of the top five suppliers' total purchase amount as a percentage of total annual purchases and the top five in sales as a percentage of total sales.

Control Variable (CV). Firm performance is influenced by a variety of internal and external factors. Firm specific control variables are essential to properly separate the casual effect of R&D subsidy. Based on relevant studies [7, 27] this study introduces firm size, and capital structure as control variables.

For specific variable definitions and measurements, please refer to Table 1.

Table 1.
Variable selection and definition.

Variables	Indicators	Definition	
Dependent variable (DV)			
Firm Performance (FP)	Return on Equity (ROE)	Net profit/total average assets×100%	
Independent variable (IV)			
Technological Innovation (TI)			
	RD intensity (RD)	R&D expenditure/operating income ×100%	Amount of R&D expenditure
	Patent (PA)	Number of patents of current year	
Moderating variable (MV)			
Supply Chain Concentration (SCC)	SCC	(Purchase ratio of the top 5 suppliers + sales ratio of the top 5 customers) /2	
Control variable (CV)			
Firm size	FA	amount of fixed asset	
Capital structure	LEV	Total liability/total asset×100%	

3.3. Data

3.3.1. Data Collection

The study population for this study includes are the legally registered public listed seed companies in China. There are two type of listed seed companies in this study, which are A share listed firm and NEEQ (National Equities Exchange and Quotations) listed firm.

The A-share market is the stock exchange market in mainland China that is open to domestic investors and foreign institutional investors through the Qualified Foreign Institutional Investor (QFII) program. The NEEQ (National Equities Exchange and Quotations) market is an OTC (over-the-counter) system for trading the shares of public limited companies incorporated in mainland China that are not listed on either the Shanghai or Shenzhen stock exchanges. NEEQ is also known as the New Third Board, is a Chinese over-the -counter (OTC) market for trading the shares of public limited companies that are not listed on any of the other stock exchanges in China.

A-share listed seed companies are chosen based on Shenwan Industry Classification Standard (2021). Under Shenwan Industry Classification standard, there is a specific industry category called "SEED". Until December 2023, there are 9 A-share listed companies in the small branch of SEED, based on Shenwan Industry Classification Standard (2021). NEEQ-listed seed companies are chosen based on codification issued by National Bureau of Statistics of China, which related with seed industry are 01-011-0111(called "Seed and Seeding activities"). There are 28 NEEQ listed seed companies, based on

NEEQ officially released classification documents (by the end of May 2023). The NEEQ official documents are following the rule of the classification of National Bureau of Statistics of China.

Therefore, the study population is 37 publicly listed crop seed companies, of which 9 are A Share listed seed companies and the remaining 28 are NEEQ listed seed companies. Considering the availability and consecutive years of data, the 34 listed companies, which listed on the capital market before year 2021, in the Chinese seed industry are selected.

3.3.2. Data Source

This study utilizes a panel dataset that spans a period from 2013 to 2022, covering multiple seed companies in China. The selection of companies and the time frame for this study were guided by the availability of comprehensive data. The data for this study were sourced from a variety of databases, including the CSMAR database (<https://data.csmar.com/>), WIND database (<https://www.wind.com.cn/>), China Seed Industry Big Data DATABASE (<http://202.127.42.47:6009/Home/BigDataIndex>), China National Intellectual Property Administration (CNIPA) (<http://epub.cnipa.gov.cn/>) and the Annual Reports of the seed companies ranging from 2013 to 2022.

4. Results and Discussions

4.1. Descriptive Statistics of Variables

To facilitate measurement and ease the effects of heteroskedasticity, this study has accurately processed the raw data. The logarithmized data will be employed for the empirical analysis. Moreover, given the presence of missing data for certain firms in specific years, this study fills in these gaps with zeros. The descriptive statistics results are displayed in Table 2.

Table 2.
Summary of Descriptive Statistics.

Variable	N	Mean	SD	Min	Max	Median	Skewness
Dependent variable							
ROE	276	6.62	12.1	-33.76	49.69	6.55	-0.25
Independent variable indicators							
PA	276	4.54	7.32	0	36	1	2.28
RD	276	5.64	4.68	0.08	28.62	4.82	2.16
Moderator							
SCC	276	38.54	19.36	6.33	83.54	37.91	0.18
Control variables							
LEV	276	37.75	16.81	2.94	78.25	37.2	0.24
FixA	276	13.06	1.2	9.32	18.33	13.07	2.05

Table 2 presents descriptive statistics for the variables analyzed in this study, derived from 276 firm-year observations of Chinese seed industry listed companies (2013–2022). The table summarizes central tendency (mean, median), dispersion (standard deviation, min–max range), and distributional properties (skewness, kurtosis). Key insights are outlined below.

Displaying in Table 2, the mean value of Company performance (ROE) is 6.62, the standard deviation (SD) value of ROA is 12.1, and median is 6.55, which means the indicator selected in this paper have a certain degree of volatility and can be analyzed in a regression analysis. The Skewness value of company performance is -0.25, which means the data is negatively skewed. There is a longer tail on the left side.

In Table 2, the median R&D intensity (RD) value (4.82) is slightly lower than the mean (5.64), suggesting a possible skewness towards higher values. Indicator RD ranges from a minimum of 0.08 to a maximum of 28.62, indicating a considerable spread in the data. Notably, the maximum value is approximately 336 times greater than the minimum value. The standard deviation (SD) of 4.68 suggests

that there is variability in RD values among the companies, with some having considerably higher or lower intensities. The positive skewness (2.16) indicates that the distribution of RD values is skewed to the right, with a tail extending towards higher values. The positive kurtosis (9.66) indicates that the distribution has heavier tails and a more peaked shape compared to a normal distribution.

In Table 2, the mean number of patents (Patent) is 4.54, indicating that, on average, companies have a moderate number of patents. The median number of patents (1) is much lower than the mean, suggesting a possible skewness towards lower values. The positive skewness (2.28) indicates that the distribution of patent values is skewed to the right, with a tail extending towards higher values. The positive kurtosis (8.44) indicates that the distribution has heavier tails and a more peaked shape compared to a normal distribution.

4.2. Benchmark Regression

By analyzing the coefficients of the primary explanatory variables obtained from the regression, it can more effectively assess the influence of the independent variables on the dependent variable. The results of the regression analysis help to clarify the relationships between variables, provide empirical support, and lay the groundwork for policy formulation and prediction.

Table 3.
Results for Benchmark Regression.

	Model 1a	Model 1b	Model 1
	ROE	ROE	ROE
RD	-1.061** (-2.456)		-1.163*** (-3.011)
PA		-0.192 (-1.621)	-0.308*** (-3.074)
FixA	-7.511*** (-2.764)	-6.148** (-2.435)	-6.881** (-2.711)
LEV	-0.093 (-1.043)	-0.086 (-0.906)	-0.076 (-0.877)
_cons	114.169*** (3.255)	91.024** (2.721)	107.276*** (3.269)
N	276	276	276
R ²	0.170	0.072	0.200
F	8.216	3.539	9.333

Note: ***P<0.01", **P<0.05", *P<0.1

From the regression model 1 in Table 3, which regarding the impact of Technological Innovation (TI) on firm performance (FP), the following results are observed. The regression coefficient of RD is -1.163, indicating that for every 1-unit increase in RD, the ROE of seed firm would decrease by 1.163 units. The regression coefficient of Patent is -0.308, indicating that for every 1-unit increase in number of patents, the ROE of seed firm would decrease by 0.308 units. when test the impact of TI on firm performance, both RD and Patent have negative effects and at 1% level are significant. Therefore, hypothesis H1 can be supported. From the regression model 1a and model 1b in Table 3, which regarding the impact of indicator RD and indicator Patent respectively. The result in model 1a shows that the RD has negative effects ($\beta=-1.061$) and at 1% level are significant ($t=-2.456$) in model 1a. Therefore, hypothesis H1a is supported. The result in model 1b shows that the Patent has negative effects ($\beta=-0.192$) but is not significant ($t=-1.621$) in model 1b. Therefore, there is no evidence to support hypothesis H1b.

The finding is aligned with the findings of Xu, et al. [28] that RD investment is not directly visible in the results. Similarly, Leung and Sharma [29] found a negative association between R&D intensity and the firm's profitability, while its influence on long-term financial performance tends to be positive. Based on the findings above in Table 3, it is plausible that there is a time lag between the RD activities

and the realization of their benefits. This delay can be explained by the fact that the RD investments do not immediately translate into increased revenues or cost savings, thus impacting ROE negatively in the short term.

Notably, regression analysis reveals a significant negative co-impact of R&D intensity and patent quantity on Return on Equity (ROE) in Chinese seed enterprises. However, when examined separately, patent count demonstrates a negative yet statistically insignificant association with ROE. It is plausible that there might be a threshold level of patents beyond which the negative impact becomes significant. When tested separately, the sample might not reach this threshold, making the effect appear insignificant. However, when combined with RD intensity, the combined effect might push the company beyond this threshold, resulting in a significant negative impact on ROE. Seed companies often face long gestation periods between R&D investment and commercialization of new products. Patents might represent potential future value, but in the short to medium term, they do not necessarily translate into immediate profits. This delay could explain the negative impact on ROE, especially when combined with high RD intensity.

Tagliatela and Barontini [30] finds that firms with pending patent applications after five years have greater sales than similar companies without applications. This phenomenon finds contextual explanation in the industry-specific protracted gestation periods between R&D investment and product commercialization. While patents represent latent value reservoirs, their conversion into tangible profits faces substantial time constraints, particularly when coupled with sustained high R&D intensity. The compounded financial pressure from continuous R&D investment and patent-related costs (including maintenance and protection expenses) creates an operational leverage effect that disproportionately impacts equity returns during the pre-commercialization phase.

4.3. Robustness Test

Robustness testing in study, particularly in statistical analysis, is a set of methods used to verify that the results of a study are reliable and not sensitive to changes in the model specification or data. Robustness Testing evaluates the resilience of evaluation methods and indicator interpretations. Specifically, it investigates whether evaluation methods and indicators maintain a consistent and stable explanation of evaluation results when certain parameters are altered. In simpler terms, arriving at a conclusion requires verifying its reliability through a series of methods. If certain conditions or assumptions are altered and the conclusion remains unchanged, it indicates that the conclusion is robust. Conversely, if the conclusion varies, it is necessary to identify the reasons behind this change and provide an explanation. Conducting robustness testing is a crucial step toward achieving widespread acceptance of research findings [31].

Table 4.
Results for Robustness Regression.

	(1)	(2)	(3)
	ROA	ROA	ROA
RD	-0.621** (-2.387)		-0.667*** (-2.813)
PA		-0.073 (-1.356)	-0.139*** (-2.799)
FixA	-4.465** (-2.505)	-3.760* (-1.991)	-4.181** (-2.439)
LEV	-0.105** (-2.496)	-0.103** (-2.199)	-0.097** (-2.343)
_cons	69.915*** (3.109)	57.485** (2.328)	66.807*** (3.084)
N	276	276	276
R2	0.210	0.096	0.230
F	10.959	3.907	11.844

Note: ***P<0.01", "**P<0.05", "*P<0.1

Comparing the regression results in (1) (ROE as indicator) in Table 3 and (2) (ROA as indicator) in Table 4, it can be seen that the direction sign and significance of regression coefficients of key variables have not changed significantly. Therefore, the robustness test is confirmed that the main results are reliable.

4.4. Lagged Effect

When constructing economic models, considering the lag of R&D investment can help to predict economic trends and company performance more accurately. Normally, the companies would receive government funds only when the company completed some specific activities, which would resulting in influence on company performance in next period instead of current period. Governments and businesses need to take into account the lag of R&D investment when formulating R&D policies and budgets to ensure long-term sustainable development [31].

Therefore, this study examined the impact of one-period and two-period lags of each independent variable to better predict their effects on company performance. This approach allows for a more detailed understanding of how the timing of R&D investments influences long-term outcomes. By incorporating lagged effects, the thesis aims to provide a robust framework for evaluating the strategic allocation of R&D resources and its subsequent impact on a company's competitive advantage and market performance. Additionally, the analysis considers potential interactions among variables to ensure a comprehensive assessment of the complex dynamics within the corporate innovation process.

Table 5.
Results of Lagged effect.

	(1)	(2)	(3)	(4)
	ROE(t=0)	ROE(t=1)	ROE(t=2)	ROE(t=3)
RD	-1.163*** (-3.011)			
PA	-0.308*** (-3.074)			
L.RD		-0.377** (-2.438)		
L.PA		-0.314*** (-2.778)		
L2.RD			0.397* (1.795)	
L2.PA			-0.138 (-1.105)	
L3.RD				0.937*** (3.478)
L3.PA				0.171 (0.833)
FixA	-6.881** (-2.711)	-3.200 (-0.980)	-2.649 (-0.650)	-4.238 (-1.021)
LEV	-0.076 (-0.877)	-0.149 (-1.588)	-0.191* (-1.934)	-0.329*** (-3.113)
_cons	107.276*** (3.269)	56.823 (1.344)	45.733 (0.858)	67.492 (1.227)
N	276	241	206	171
R ²	0.200	0.089	0.062	0.157
F	9.333	3.958	2.542	6.159

Note: ***P<0.01", **P<0.05", *P<0.1; Dependent variable = ROE at t = 0 (current year), t = 1 (1-period lag), t = 2 (2-period lag), t=3(3-period lag).

As shown in Table 5, in column (1), both RD and Patent have significant negative coefficients at the 1% level. In column (2) with a one-year lag, both L.RD and L.Patent are still negative but with lower significance (L.RD at 5%, L.Patent at 1%). In column (3) with a two-year lag, L2.RD is positive and significant at 10%, while L2.Patent is negative but not significant. This suggests that after two periods, the negative effect of RD starts to reverse, but patents still don't show a significant impact. Column (4) with a three-year lag shows L3.RD is positive and highly significant (1% level), while L3.Patent is positive but not significant. The R-squared increases again, which might indicate that the model is better capturing the full impact of R&D investments on ROE. The results here show that RD has an immediate negative impact, which turns positive after two and three years. Patents, however, remain negative in the short term but turn positive and lose significance in longer lags.

The initial negative impact of R&D on ROE aligns with the previous findings that argument about delayed benefits. The shift to positive coefficients at lags 2 and 3 supports the time lag hypothesis. Patents don't have a delayed positive effect as R&D does, possibly due to maintenance costs or lack of immediate commercialization. In seed industry where commercialization takes longer, it suggests that patents aren't the right measure of immediate value.

4.5. Moderating Effect Results

The sign and coefficients of the interact term determine whether the moderating effect weaken or strength the relationship between dependent variable and independent variable. When the coefficient of the interact term is positive, it increases the relationship in comparison to the direct effect coefficient. Otherwise, it weakens the relationship [32, 33].

Table 6.
Results for moderating effect.

	(1)	(2)
	ROE	ROE
Direct effect		
RD	-1.162*** (-6.061)	-0.716** (-2.029)
PA	-0.308*** (-2.972)	-0.149 (-0.840)
SCC	0.002 (0.039)	0.097 (1.237)
Interactions		
RD*SCC		-0.013* (-1.672)
PA*SCC		-0.006 (-0.995)
Control Variables		
FixA	-6.878*** (-4.036)	-6.276*** (-3.636)
LEV	-0.076 (-1.219)	-0.067 (-1.081)
_cons	107.139*** (4.714)	95.822*** (4.101)
N	276	276
R ²	0.200	0.215
F	11.822	9.131

Note: ***P<0.01", "**P<0.05", *P<0.1.

The results shown in Table 6 revealed that the coefficient of determination on moderating model is 0.215, which indicates that the combination of technological innovation (TI) and supply chain concentration (SCC) with their interactions can explain variation in ROE of the Chinese listed seed companies. The overall R² shows that the variables jointly account for 21.5% variations in ROE. The 9.131 value of F, indicates that the model is fit and the relationship between dependent variable and the independent variables was not due to chance but well-selected explanatory variables. Also, based on the result on Table 6, interaction term RD*SCC are significant. The moderate effect weakens the negative relationship between RD and ROE. Consequently, this study accepts the hypothesis H₂, which states that SCC moderate the relationship between TI and ROE.

Chen and He [7] found that supply chain concentration moderates the relationship between R&D investment and current corporate performance at a significant level of 1%. The possible explanation is that due to the unique characteristics of seed industry, it is associated with a high degree of supply chain concentration. A high degree of supplier concentration implies that the company has established close cooperative relationships with a few high-quality suppliers. Through long-term cooperation with these suppliers, seed companies can optimize procurement costs and enhance production efficiency, thereby partially offsetting the negative impact of R&D intensity on ROE (Return on Equity). Meanwhile, a high degree of customer concentration indicates that the enterprise relies on a few major customers. By engaging in long-term cooperation with these major customers, the company can enhance its brand recognition and market share, which in turn increases the added value of its products and alleviates the negative impact of RD intensity on ROE.

5. Conclusion

This study examined the temporal dynamics between technological innovation indicators (RD intensity and patent) and performance (ROE) of seed companies, as well as the moderating role of supply chain concentration (SCC). Key findings reveal a significant negative relationship between RD intensity (RD), patent (PA), and ROE ($\beta = -1.163$, $p < 0.01$; $\beta = -0.308$, $p < 0.01$), suggesting short-

term cost absorption from innovation activities in seed industry. However, time-lagged analyses show a delayed positive effect: RD intensity exhibits significant ROE increase starting at a two-period lag ($\beta = 0.397$, $p < 0.05$), while patent show nonsignificant positive trends from a three-period lag ($\beta = 0.171$, $t = 0.833$). These results align with innovation diffusion theory, where technological commercialization requires temporal and organizational resources [28].

Furthermore, supply chain concentration (SCC) plays a significant moderating role by weakening the negative relationship between RD and ROE. This suggests that SCC can help mitigate the short-term negative impact of R&D investments on ROE, thereby facilitating a better balance between short-term cost pressures and long-term innovation benefits.

Considering the characteristics of seed enterprises, these findings hold important implications. Seed enterprises are often characterized by high R&D intensity and a focus on technological innovation. They play a crucial role in driving agricultural productivity and ensuring national food security. The lagged positive effect of R&D intensity on ROE indicates that sustained investment in R&D is essential for seed firms to enhance the long-term competitiveness. Additionally, the moderating effect of SCC suggests that optimizing supply chain management can help seed enterprises better leverage their R&D investments and improve overall performance. Seed firms are also subject to unique industry features, such as high entry barriers, regional specificity, and seasonal production and sales cycles. These characteristics require seed enterprises to strategically manage their R&D and supply chain activities to maximize efficiency and effectiveness. Meanwhile, the seasonal nature of seed production and sales necessitates precise planning and coordination to ensure timely supply and efficient resource utilization.

In conclusion, this study highlights the importance of R&D investments for seed enterprises and the role of supply chain concentration in moderating the relationship between R&D and corporate performance. Seed enterprises should continue to invest in R&D to drive innovation and enhance their core competitiveness. At the same time, they should optimize their supply chain management to better support their R&D efforts and improve overall performance. Future research could further explore the specific mechanisms through which SCC influences the R&D-performance relationship in seed enterprises, as well as the impact of other industry-specific factors on this relationship.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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References

- [1] R. M. Pei, C. Zhang, and K. H. Chen, "Promote deep integration of innovation chain and industry chain by improving national innovation systems of crop seed industry," *Bulletin of Chinese Academy of Sciences (Chinese Version)*, vol. 37, no. 7, pp. 967-976, 2022. <https://doi.org/10.16418/j.issn.1000-3045.2022.0705>
- [2] N. Zhang and L. Y. Zhang, "Research on the construction of a demand-driven global value chain in the seed industry based on a super-large-scale market," *Seed*, vol. 42, no. 5, pp. 148-156, 2023. <https://doi.org/10.1016/j.seed.2023.03.003>
- [3] UN, "The state of food security and nutrition in the world 2020: Transforming food systems for affordable healthy diets. United Nations," Retrieved: <https://www.fao.org/3/ca9692en/CA9692EN.pdf>. [Accessed 2020].
- [4] F. Yi, D. Sun, and Y. Zhou, "Grain subsidy, liquidity constraints and food security—Impact of the grain subsidy program on the grain-sown areas in China," *Food Policy*, vol. 50, pp. 114-124, 2015. <https://doi.org/10.1016/j.foodpol.2014.11.003>
- [5] S. Gong, B. Wang, Z. Yu, and Z. Cui, "Does seed industry innovation in developing countries contribute to sustainable development of grain green production? Evidence from China," *Journal of Cleaner Production*, vol. 406, p. 137029, 2023. <https://doi.org/10.1016/j.jclepro.2023.137029>

- [6] R. Ji, J. Yu, and H. Ruan, "The impact of enterprise size and R&D investment on innovation performance: Based on the perspective of credit environment and knowledge stock," *East China Economic Management*, vol. 34, no. 9, pp. 43-54, 2020. <https://doi.org/10.16381/j.cnki.issn1003-319x.2020.09.005>
- [7] C. Chen and Q. He, "The impact of R&D investment and supply chain concentration on the performance of seed industry enterprises," *Journal of Hunan Agricultural University*, vol. 22, no. 04, pp. 86-92, 2021. [https://doi.org/10.13331/j.cnki.jhau\(ss\).2021.04.011](https://doi.org/10.13331/j.cnki.jhau(ss).2021.04.011)
- [8] R. D. Zhang, "Technological innovation and enterprise value chain upgrade: The moderating role of driving subject factors," Master's Thesis, Xi'an University of Technology, 2019.
- [9] H. D. Trieu, P. Van Nguyen, T. T. Nguyen, H. M. Vu, and K. Tran, "Information technology capabilities and organizational ambidexterity facilitating organizational resilience and firm performance of SMEs," *Asia Pacific Management Review*, vol. 28, no. 4, pp. 544-555, 2023. <https://doi.org/10.1016/j.apmr.2023.02.002>
- [10] E. M. Kamal, E. C. Lou, and A. M. Kamaruddeen, "Effects of innovation capability on radical and incremental innovations and business performance relationships," *Journal of Engineering and Technology Management*, vol. 67, p. 101726, 2023. <https://doi.org/10.1016/j.jengtecman.2023.101726>
- [11] A. Mendoza-Silva, "Innovation capability: A systematic literature review," *European Journal of Innovation Management*, vol. 24, no. 3, pp. 707-734, 2021. <https://doi.org/10.1108/EJIM-01-2020-0396>
- [12] C. Camisón and A. Villar-López, "Organizational innovation as an enabler of technological innovation capabilities and firm performance," *Journal of Business Research*, vol. 67, no. 1, pp. 2891-2902, 2014. <https://doi.org/10.1016/j.jbusres.2012.06.004>
- [13] M. Sarfraz, L. Ivascu, M. I. Abdullah, I. Ozturk, and J. Tariq, "Exploring a pathway to sustainable performance in manufacturing firms: The interplay between innovation capabilities, green process, product innovations and digital leadership," *Sustainability*, vol. 14, no. 10, p. 5945, 2022. <https://doi.org/10.3390/su14105945>
- [14] S. Sylvie, *The company continues to improve the potential technical level and complete the company's technology accumulation*. New York, USA: Springer, 2017.
- [15] P. J. Sher and P. Y. Yang, "The effects of innovative capabilities and R&D clustering on firm performance: the evidence of Taiwan's semiconductor industry," *Technovation*, vol. 25, no. 1, pp. 33-43, 2005. <https://doi.org/10.1016/j.technovation.2003.12.001>
- [16] X. Li and B. Yu, "Research on the dynamic evolution simulation of technological innovation strategy and technological innovation capability of latecomer enterprises facing technological leapfrogging," *Journal of Science and Management of S.ĀT*, vol. 38, no. 11, pp. 85-102, 2017.
- [17] N. Zhang, "The development of Chinese seed industry: From company value chain upgrading perspective," *Frontiers in Business, Economics and Management*, vol. 10, no. 1, pp. 34-37, 2023. <https://doi.org/10.1007/s42380-023-00205-7>
- [18] Y. H. Kim and D. Henderson, "Financial benefits and risks of dependency in triadic supply chain relationships," *Journal of Operations Management*, vol. 36, pp. 115-129, 2015. <https://doi.org/10.1016/j.jom.2015.01.002>
- [19] S. Wei, C. Deng, H. Liu, and X. Chen, "Supply chain concentration and financial performance: The moderating roles of marketing and operational capabilities," *Journal of Enterprise Information Management*, vol. 37, no. 4, pp. 1161-1184, 2024. <https://doi.org/10.1108/JEIM-07-2023-0356>
- [20] M. Chen, X. Tang, H. Liu, and J. Gu, "The impact of supply chain concentration on integration and business performance," *International Journal of Production Economics*, vol. 257, p. 108781, 2023. <https://doi.org/10.1016/j.ijpe.2023.108781>
- [21] C. K. S. Keter, J. Y. Cheboi, D. Kosgei, and A. K. Chepsergon, "Financial performance and firm value of listed companies: Financial performance measure ROA versus ROE," *Journal of Business, Economics and Management Research Studies*, vol. 1, no. 4, pp. 1-11, 2023.
- [22] J. Hagel, J. S. Brown, A. Ranjan, and D. Byler, *Success or struggle: ROA as a true measure of business performance*. United States: Deloitte University Press, 2013.
- [23] K. Si, X. L. Xu, and H. H. Chen, "Examining the interactive endogeneity relationship between R&D investment and financially sustainable performance: Comparison from different types of energy enterprises," *Energies*, vol. 13, no. 9, p. 2332, 2020. <https://doi.org/10.3390/en13092332>
- [24] Y. Hong, D. Niu, B. Xiao, and L. Wu, "Comprehensive evaluation of the technology innovation capability of China's high-tech industries based on fuzzy borda combination method," *International Journal of Innovation Science*, vol. 7, no. 3, pp. 215-230, 2015. <https://doi.org/10.1260/1757-2223.7.3.215>
- [25] A. Reshid, P. Svensson, and N. Steinbach, "The long-term effects of R&D subsidies on firm performance: Evidence from a regression discontinuity design," *Economics of Innovation and New Technology*, pp. 1-24, 2024. <https://doi.org/10.1080/10438599.2024.2351136>
- [26] H. Shi, W. Zhang, and W. Xu, "The impact of supply chain concentration on the performance of enterprise digital transformation," *Science and Management*, vol. 44, no. 1, pp. 18-23, 2024.
- [27] S. A. Basit, T. Kuhn, and M. Ahmed, "The effect of government subsidy on non-technological innovation and firm performance in the service sector: Evidence from Germany," *Business Systems Research: International Journal of the Society for Advancing Innovation and Research in Economy*, vol. 9, no. 1, pp. 118-137, 2018. <https://doi.org/10.2478/bsrj-2018-0010>

- [28] J. Xu, F. Liu, and Y.-h. Chen, "R&D, advertising and firms' financial performance in South Korea: Does firm size matter?," *Sustainability*, vol. 11, no. 14, p. 3764, 2019. <https://doi.org/10.3390/su11143764>
- [29] T. Y. Leung and P. Sharma, "Differences in the impact of R&D intensity and R&D internationalization on firm performance—Mediating role of innovation performance," *Journal of Business Research*, vol. 131, pp. 81-91, 2021. <https://doi.org/10.1016/j.jbusres.2021.03.060>.
- [30] J. Tagliatalata and R. Barontini, "SMEs and patents: Is it worth it? A longitudinal analysis of the patent-performance relationship," *Journal of Economics and Business*, vol. 128, p. 106147, 2024. <https://doi.org/10.1016/j.jeconbus.2024.106147>
- [31] X. Y. Liu, "Robustness tests! Robustness tests!," Retrieved: <https://www.lianxh.cn/news/32ae13ec789a1.html>. [Accessed 2020.
- [32] X. Zhu, J. Wang, B. Liu, and X. Di, "Inventory stickiness, environmental dynamism, financial constraints and survival of new SMEs in China," *Journal of Manufacturing Technology Management*, vol. 32, no. 2, pp. 400-422, 2021. <https://doi.org/10.1108/JMTM-05-2020-0305>
- [33] D. M. Gligor, "The role of supply chain agility in achieving supply chain fit," *Decision Sciences*, vol. 47, no. 3, pp. 524-553, 2016. <https://doi.org/10.1111/dec.12181>