

Article

The Innovation Plight and Operational Efficiency of Chinese Manufacturing Enterprises: From the Perspective of Risk Tolerance, Expectation, and Profitability

Yanfei Shu and Yaxin Yang * 

School of Economics, Minzu University of China, Beijing 100081, China; 2007076@muc.edu.cn

* Correspondence: 23300032@muc.edu.cn

Abstract: With uncertainty intensifying the international technological innovation environment, the innovation situation of Chinese manufacturing enterprises has been impacted. Based on 12,781 micro panel data in 2011–2020 of 2347 Chinese A-share manufacturing listed enterprises, this paper empirically analyzes the impact of innovation plight faced by enterprises on operational efficiency. The innovation plight in this article refers to the degree to which the actual innovation performance of enterprises has not reached the expected innovation performance or is introduced by an innovation gap, measured by the difference when actual innovation performance is lower than the expected innovation performance. The empirical results show that the innovation plight of manufacturing enterprises significantly inhibits operational efficiency by reducing their risk tolerance, development ability expectation, and profitability. After using a series of tests, such as the instrumental variable method, replacing the dependent variable, and changing the parameters for measuring the independent variable, the conclusion is still robust. In addition, the results illustrate that the inhibitory effect of innovation plight on operational efficiency is more obvious for non-state-owned enterprises, small and medium-sized enterprises, high-tech enterprises, and enterprises in the eastern region. Finally, we formulate some relevant management suggestions.

Keywords: manufacturing enterprises; innovation plight; operational efficiency



Citation: Shu, Y.; Yang, Y. The Innovation Plight and Operational Efficiency of Chinese Manufacturing Enterprises: From the Perspective of Risk Tolerance, Expectation, and Profitability. *Sustainability* **2024**, *16*, 4916. <https://doi.org/10.3390/su16124916>

Academic Editors: Vladimíra Biňasová and Branislav Micieta

Received: 17 April 2024

Revised: 24 May 2024

Accepted: 3 June 2024

Published: 7 June 2024



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1. Introduction

With the profound adjustment of economic globalization, the main driving forces of globalization are diverging and changing. In order to cope with the risk of power transfer [1], traditional developed countries rely on hegemony to push their interests to the extreme of protectionism [2]. Currently, advanced technology innovation is the key engine of economic growth for various countries. Therefore, it has become an important area for some developed countries to restrain the development of emerging countries, making technology shift from human-shared globalism to technological nationalism [3]. Indeed, the global flow of technological elements has improved the recent speed of China's economic development. However, in recent years, some manufacturing enterprises in China have fallen into the plight of technological innovation when technological nationalism is rampant [4].

Under the background above, in terms of theoretical construction and sustainability of industrial development, it is necessary for us to answer the following questions: What is the situation of technological innovation plight in Chinese manufacturing enterprises? What impact does the innovation plight have on the operational efficiency of manufacturing enterprises? And what is the mechanism behind the impact?

In order to answer these questions, this article has conducted the following theoretical and empirical work: First, it has analyzed and verified empirically the negative impact of technological innovation plight on operational efficiency. Second, in particular, it has analyzed and tested empirically that the technological innovation plight of enterprises has

an impact on operational efficiency through risk-taking, expected development capability, and profitability. Third, it has analyzed and tested the differences in the impact among different types of enterprises from the perspectives of enterprise, industry, and region.

There are many studies closely related to this article, mainly divided into three categories.

The first type is the research on technological innovation. The existing research on technological innovation mainly focuses on three aspects:

(1) Research on the impact of technological innovation on factors related to enterprise management and development. Most articles point out the multiple positive impacts of technological innovation. Hervás-Oliver and Sempere-Ripoll [5] found the positive impact of technological process innovation on organizational innovation. Wang and Sun [6] also emphasized the positive impact of technological innovation on enterprise growth. Interestingly, there are relatively few discussions on the negative impact of technological innovation. Zhang and Aumeboonsuke [7] found that technological innovation reduces enterprises' risk-taking, which is detrimental to their performance;

(2) Research on exploring the factors influencing technological innovation from multiple perspectives. Zou [8] discussed the relationship between corporate digitization and technological innovation, concluding that the positive impact of digitization is more obvious on traditional technological innovation than on green technological innovation. From a resource-based perspective, Liu and Xiao [9] found that dual innovation human capital has a significant impact on the technological innovation efficiency of big data enterprises. Interestingly, Henao-Garía and Montoya [10] found that management innovation has a negative moderating effect on the relation between technological innovation and performance in Colombia. This work advances the research on dynamic capability perspectives to analyze technological innovation in emerging economies;

(3) Research on the comparison and combination of technological innovation and non-technological innovation. This type of research also occupies a significant proportion in the field of technological innovation. Aboal and Garda [11] found that the roles of technological innovation and non-technological innovation in the manufacturing and service industries are not the same, while Martín-Ríos et al. [12] explained how technological innovation and non-technological innovation bind together in a correlated way. And Gallegos and Miralles [13] concluded that non-technological innovation can affect technological innovation in Peru, encouraging companies to support activities that are not necessarily related to R&D to promote technological innovation.

The literature in the field of technological innovation is abundant and provides important reference value for this article.

The second type is articles that research operational efficiency. Operational efficiency, as one of the main indicators for evaluating the level of enterprise management, is also a hot topic for scholars. A large number of scholars discussed the factors affecting the operation efficiency of enterprises, such as the Environmental, Social, and Governance (ESG) performance [14], strategic flexibility [15], internal audit function (IAF) quality [16], and cash flow [17], etc. The discussion on the enterprise operation efficiency has formed a system, but the innovation situation of the enterprise has not been taken into account.

The third type of research is directly related to this article, which is the research on the situation of enterprise technological innovation. But, such research is presently scarce. Lian et al. [18] explored the impact of the innovation situation on corporate strategic response based on the theory of corporate behavior. Zhan and Ma [19] explored the "low-end locked" dilemma in corporate innovation and studied the impact of high-tech enterprise cultivation policy on this dilemma. The research on the relationship between innovation plight and operational efficiency is conducive to enriching research in this area.

Overall, there is limited research on the situation of technological innovation. And currently, there are no articles discussing the correlation between technological innovation plight and the operational efficiency of enterprises yet.

How, then, do we measure innovation plight authentically? We refer to the three-step calculation method from Lian et al. [18]. The premise is that we use the number of

patent applications of enterprises as basic data, including invention patents and utility model patents.

Step 1: Determine the actual innovation performance of enterprises (AIP). For fear of the volatility of the technological innovation process, the period $t - 1$ AIP is the average number of patent applications from period $t - 2$ to period t . Step 2: Build the innovation performance expectation (EIP). The period $t - 1$ EIP is the weighted sum of the average patent applications of the industry in which the enterprises are located during the periods $t - 2$ and $t - 3$. The weight parameter β is set as 0.5. In the robustness test later, the parameters will be changed to 0.6 and 0.4 to test the core conclusion. Step 3: Calculate the innovation plight of period $t - 1$. AIP_{t-1} minus EIP_{t-1} . If the difference value is less than 0, take the absolute value as the observation value of the enterprise's innovation plight. If the difference value is more than 0, take 0 as the observation value of the innovation plight. The Steps above are summarized in Figure 1.

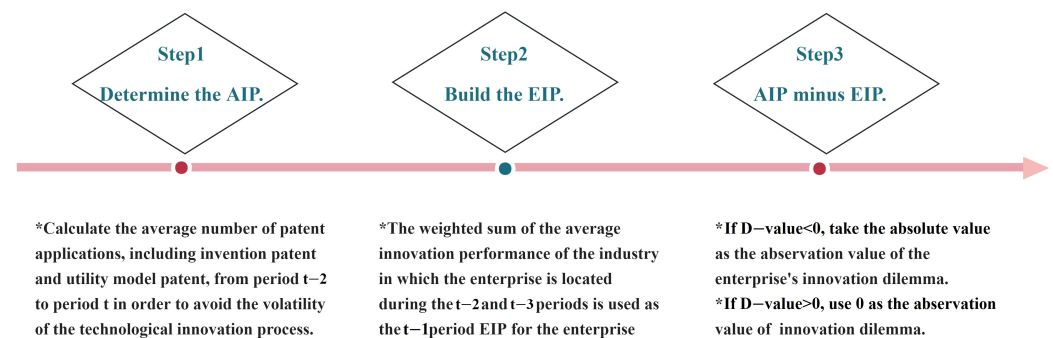


Figure 1. The steps of calculating the innovation plight. The symbol * represents detailed explanation.

Accordingly, when an enterprise falls into the innovation plight, it means the enterprise has reduced innovation competitiveness in its industry.

Based on the data on innovation plight, the article draws a distribution map of the innovation plight of manufacturing enterprises in China. Combining regional data and considering its integrity, the regional distribution maps (Figures 2 and 3) of innovation plight in 2012 and 2020 are as below.

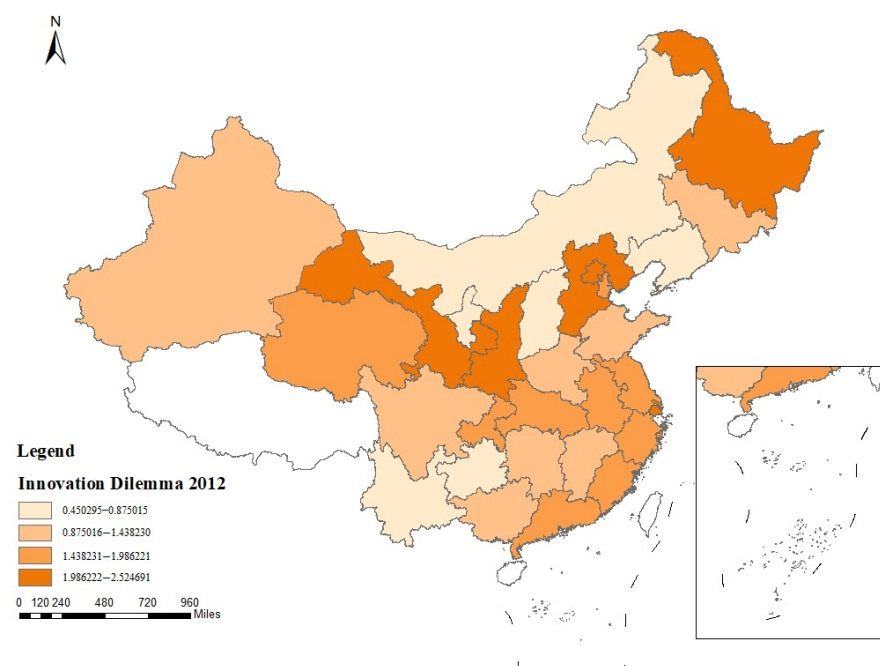


Figure 2. The regional distribution of innovation plight of Chinese A-share manufacturing listed companies in 2012.

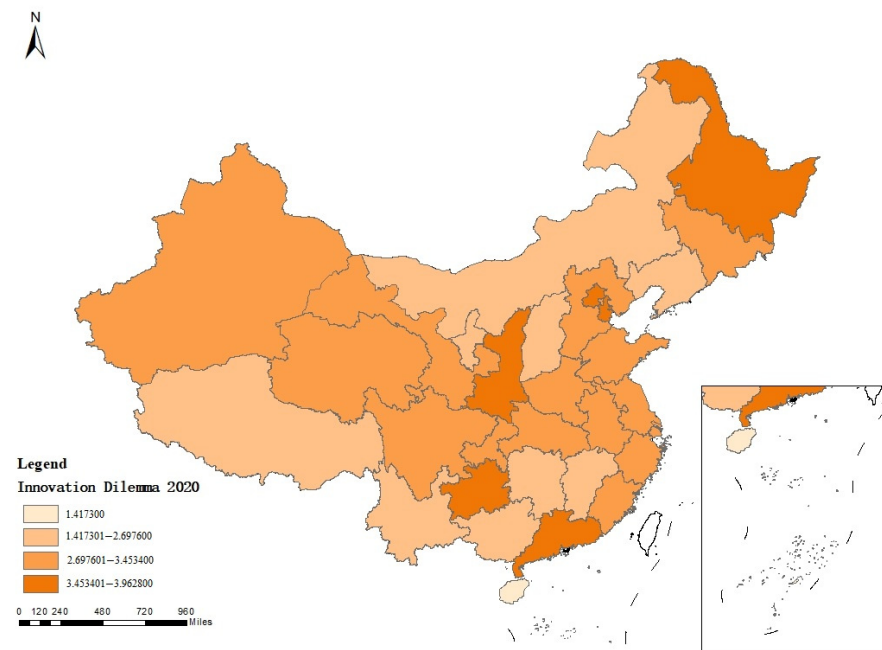


Figure 3. The regional distribution of innovation plight of Chinese A-share manufacturing listed companies in 2020.

According to Figures 2 and 3, in general, there are obvious differences in the distribution of innovation plight between 2012 and 2020. The group distance of the horizontal group of innovation plight between regions in 2020 becomes wider, and the value range of the innovation plight of enterprises in 2020 expands. These phenomena indicate that the overall level of innovation plight in 2020 is higher than in 2012.

So why has the innovation plight become more severe over time? Under the background that instability of the international technological innovation environment is increasing, independent R&D has gradually become the main way of technological innovation for Chinese manufacturing enterprises. However, at the same time, the continuous progress of the technological level led to the rising difficulty of technological innovation. In other words, the diminishing marginal technological innovation of manufacturing enterprises has become the only way before making major technological breakthroughs. To be noted, the deterioration of innovation situation at this time cannot be equated with the decline of technological innovation level.

In particular, according to Figures 2 and 3, the provincial administrative regions with the highest level of innovation plight in 2012 and 2020 mainly involve the regions with leading economic development and the regions where old industrial cities are located. For example, in 2012, the provincial-level administrative regions with the highest level of innovation plight included Beijing and Shanghai, as well as Gansu, Shaanxi, and Heilongjiang provinces. In 2020, the provincial-level administrative regions with the highest level of innovation plight involve Beijing, Tianjin, Guangdong Province, and Shaanxi and Heilongjiang provinces. Currently, enterprises in old industrial areas have long faced innovation plight due to the great pressure of industrial structure transformation and technological upgrading [20].

How do we understand the distribution map (Figures 2 and 3) that shows that enterprises in regions with higher economic development levels are faced with more serious innovation plight?

First, explore the general reasons behind this law: According to the theory of new economic geography, in the development of high-tech industry, the flow of various input factors will promote the geographical agglomeration of economic activities of enterprises and related organizations in the industry. The correlation effect between different enterprises in the industrial chain will also promote the preference of enterprises to carry out

their production activities in regions with larger market sizes [21]. The actual situation is consistent with the theory. In reality, the spatial distribution of China's high-tech industry is concentrated in the eastern coastal areas with high economic development levels, such as the Bohai Rim area with Beijing as the center, the Yangtze River Delta area with Shanghai as the head, and the Pearl River Delta area with Shenzhen and Guangzhou as the center [22].

In addition, the high-tech industry has relatively high technical difficulty and innovation requirements, which makes it easier to face innovation bottlenecks. And regions with higher levels of economic development have more enterprises, which means greater competitive pressure and higher levels of technological innovation.

Based on the above reasons, economically developed areas with concentrated high-tech industries inevitably face more severe innovation plight.

Compared with the previous research, the marginal contribution of this paper is mainly reflected in the following two aspects:

First, in terms of theoretical construction, this paper depicts the current situation of the innovation plight of Chinese manufacturing enterprises. It enriches the research on the enterprises' innovation situation. And it also finds the relationship between innovation plight and the operational efficiency of manufacturing enterprises and the mechanism behind it. Current research pays less attention to the innovation situation of enterprises, especially the impact of innovation plight on the operational efficiency of enterprises. This paper makes up for this gap.

Second, from the perspective of manufacturing enterprises, the conclusion of this article has economic significance for company management and operation. In particular, this article found that the negative impact of innovation plight on operational efficiency is heterogeneous among enterprises in different ownership, scale, development stages, and regions. The conclusions and suggestions in Section 5 of this article are undoubtedly conducive to the company's management and operation.

The contents of the following sections of the article are as follows. The second part is a theoretical analysis and research hypothesis. The third part introduces the data source, model setting, related variables, and their measurement. The fourth part shows the empirical results and a series of robustness tests, then further carries out mechanism analysis and heterogeneity analysis. The fifth part emphasizes the conclusion of empirical analysis and provides further discussion.

2. Theoretical Analysis and Research Hypotheses

2.1. *The Impact of Innovation Plight on the Operational Efficiency*

Continuous technological innovation is an important means for manufacturing enterprises to improve their core competitiveness. On the one hand, the popularization of production technology has continuously improved social production efficiency, leading to more intense competition among manufacturing enterprises [23]. In order to win a place in the industry, enterprises must continue to carry out technological innovation. On the other hand, consumers' higher living standards and more requirements for products also force manufacturing enterprises to carry out continuous technological innovation. The more exquisite product design and more useful functions can bring the company stronger competitiveness and greater profits [24].

However, China's manufacturing industry learns foreign advanced technology in the initial stage of technological innovation. Therefore, the harsh environment of international technological innovation now causes some domestic manufacturing enterprises to fall into an innovation plight [25]. The innovation plight reduces the profit margins of enterprises, which is not conducive to their sustainable development and puts them at a disadvantage in fierce market competition.

How, then, do we measure the impact of innovation plight on business operations? Operational efficiency is a reasonable choice. It can not only reflect the ability of enterprises to use resources but also indicate their market competitiveness. Therefore, the impact of an event or a decision on the development of enterprises can be judged by operational efficiency.

The innovation plight may inhibit operational efficiency. The operation system requires sufficient cash flow to support [17]. But the innovation plight will lead to a lower market share. Then the decrease in the profitability and development ability of the enterprise after that may affect the operational efficiency. In the short term, if the increase in R&D does not receive sufficient returns, the technological innovation plight is more likely to have a negative impact on the operational efficiency of enterprises. Critically, in the long run, if a company's R&D achieves results and receives commercial returns, the improvement of its technological innovation situation may have a promoting effect on operational efficiency. In this situation, the enterprise has already or is about to remove or overcome plight. However, if the manufacturing companies cannot escape the innovation plight in the long term and continue to invest in R&D, the impact of innovation plight on the company's operation may even be fatal.

Based on the above analysis, hypothesis 1 was proposed:

H1. *For manufacturing enterprises, innovation plight has a negative impact on operational efficiency.*

2.2. Mechanisms of Action

Based on the capability evaluation system of the enterprises, this paper analyzes the ways in which innovation plight affects operational efficiency.

The competitiveness of an enterprise can be evaluated from multiple perspectives and indicators. Actually, financial indicators are often considered the most direct and effective judgment criteria. They usually involve solvency [26], development ability, management ability, and profitability of the enterprise, which are regarded as important decision-making references for investors or enterprise managers [27]. The financial indicators not only reflect the results of the enterprise's past operations, but also can be used as a reference for judging the future development of the enterprise [28].

Usually, risk-taking capacity, development capacity and profitability are used to evaluate the business operation of an enterprise. These three capabilities of enterprises are not isolated but systematic. For example, in fierce market competition, higher profitability of an enterprise will obtain higher expectations for its development ability from the investors. And the better expectation is beneficial for the enterprise to attract more adequate sources of capital, and thus improve the risk bearing ability. Obviously, the financial indicators of these three capabilities can jointly reflect a company's operational ability from multiple perspectives.

2.2.1. Innovation Plight Suppresses Operational Efficiency through Risk-Taking Capacity

The ability of enterprises to bear financial risks is an important link to maintaining operational efficiency [17]. According to the meaning of innovation plight in this article, when an enterprise falls into the innovation plight, it means the enterprise has less competitiveness in its industry. On the one hand, the disadvantaged position in the industry will make it difficult for the enterprise to obtain loans. On the other hand, disadvantaged enterprises will be squeezed by advantageous enterprises and obtain fewer resources [29]. At this time, the fragile capital chain and tight resources will be likely to inhibit operational efficiency.

Based on the above analysis, hypothesis H2a was proposed:

H2a. *Innovation plight inhibits the operational efficiency of firms by reducing their anti-risk ability.*

2.2.2. Innovation Plight Suppresses Operational Efficiency by Development Capacity Expectation

To evaluate a business, investors care about both the current and expected future innovation ability of an enterprise. And the expectation of enterprises' development ability is also one of the important abilities that affect the operational efficiency of enterprises [30].

The evaluation indicators of enterprise development ability usually include the rate of capital preservation and appreciation, the rate of capital accumulation, the growth rate of total assets [31], etc. These indicators mainly evaluate the value of enterprises from

the perspective of owners' equity and assets. When the technological innovation of an enterprise encounters the plight, the market competitiveness of the enterprise is likely to decrease. In the foreseeable future, the revenue and profit will be affected [32]. Then, the expectations from various sectors of society for the development ability of the enterprise diminish, which further affects the operational efficiency.

Based on the above analysis, hypothesis H2b was proposed:

H2b. *Innovation plight affects the operational efficiency of the firm by reducing the expectations of the firm's development capability.*

2.2.3. Innovation Plight Suppresses Operational Efficiency through the Profitability

Profitability is a factor that can directly affect the operational efficiency of enterprises [33], especially as enterprises encounter innovation plight. At this time, the product update speed of the enterprise is slower than other enterprises in the same industry, leading to a lower market share. The disadvantaged position is more likely to lead to a lack of revenue growth. In the long run, the operation and maintenance of the operation system will be affected, which further inhibits operational efficiency.

Based on the above analysis, hypothesis H2c was proposed:

H2c. *Innovation plight negatively influences the operational efficiency of firms by reducing their profitability.*

Overall, theoretical mechanism analysis shows that the innovation plight faced by manufacturing enterprises may inhibit operational efficiency by reducing their risk tolerance, development ability expectation, and profitability, as shown in Figure 4.

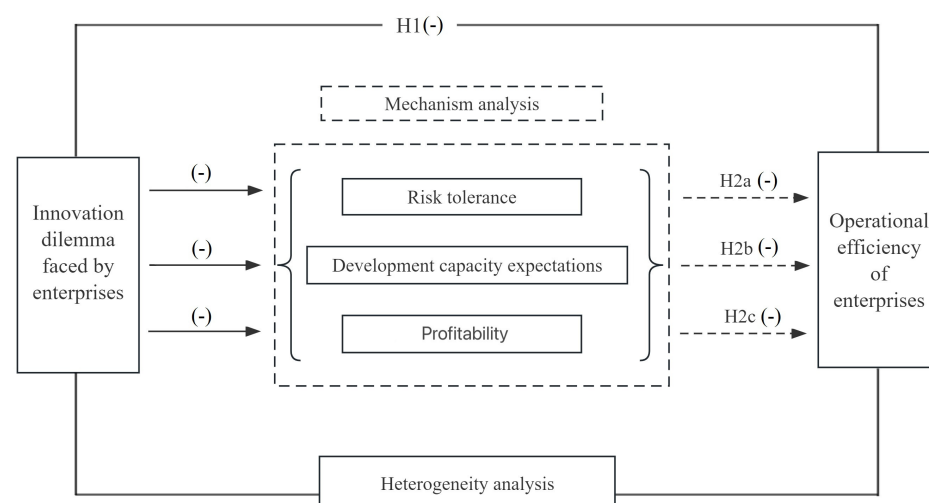


Figure 4. Diagram of mechanism analysis. Within the dotted line are the mechanism variables.

2.3. The Heterogeneous Impact of Innovation Plight on Operational Efficiency of Manufacturing Enterprises

The differences in the impact of innovation plight on operational efficiency are analyzed in this paper from various aspects. Different enterprises may have different ownership structures and scales and are in different development stages. The industrial attributes and regions of the enterprises will also be different. Therefore, the impact of the innovation plight on operational efficiency is heterogeneous.

At the firm level, three factors can be used to assess the heterogeneity of innovation plight affecting operational efficiency: the ownership, the scale, and the life cycle of the enterprises.

In terms of ownership, non-state-owned enterprises and state-owned enterprises are the two main economic subjects in the background of the Chinese system. The difference in

ownership leads to different social roles and obligations. In addition to pursuing economic benefits, state-owned enterprises need to bear more social responsibilities. But, they also have more resource endowments, easier access to external market resources, and stronger innovation capabilities [34]. And non state-owned enterprises are more vulnerable in the fierce market competition due to relatively insufficient resource endowments and access to resources. Therefore, there is likely to be a lack of resources and capabilities for non-state-owned enterprises to cope with innovation plight. The operational efficiency of non-state-owned enterprises may be more affected by the innovation plight.

For the scale of the enterprise, small enterprises have insufficient advantages in market competition, relatively small living space, and high sensitivity to innovation plight. In comparison, large enterprises have a stronger ability to withstand and cope with innovation plight. Therefore, the impact of innovation plight on the operational efficiency of small enterprises may be more significant.

As far as the enterprise's life cycle is concerned, it can be divided into the initial stage, ascend stage, mature stage, and decline stage [35].

For the ascend stage, in order to improve their market competitiveness and expand their scale, enterprises in the ascend stage have strong motivation and demand to expand their market share. At this time, corresponding to the significant promotion effect of technological innovation on the development of enterprises, the impact of innovation plight on the operational efficiency of enterprises in the ascend stage is also significant.

In contrast, enterprises in the recession period have relatively poor financial status and profitability. They are more likely to face a lack of motivation for technological innovation and a higher possibility of innovation plight. However, the relatively fragile financial status reduces the ability of these enterprises to withstand innovation plight. Therefore, the innovation plight of enterprises in the recession period will have a more obvious inhibitory effect on business efficiency.

For the initial stage, on the one hand, start-up enterprises rely on initial endowments to operate. Compared with the situation of technological innovation, the establishment of business modes and business models is the main factor affecting the operational efficiency of enterprises at this time [36]. On the other hand, start-up enterprises either rely on existing innovation achievements to establish enterprises or technological innovation is in the initial stage. The innovation situation may have little influence on the operation efficiency of enterprises in the initial stage.

For mature enterprises, on the one hand, they may have established a relatively stable business model. Their operational efficiency is less sensitive to innovation difficulties. On the other hand, their economic benefits and financial status are relatively stable, and they have the experience and ability to cope with innovation plight. Therefore, the operation efficiency of the mature enterprises may be less affected by the innovation plight.

Based on the above analysis, hypothesis H3a was proposed:

H3a. *For private enterprises, small and medium-sized enterprises, and enterprises in the ascend and decline phases, innovation plight has a more significant negative effect on operational efficiency.*

From the perspective of whether an enterprise belongs to a high-tech industry, the heterogeneity at the industry level is investigated. In the manufacturing industry, the technological progress of the high-tech industry is faster, and the replacement frequency is higher. The fierce competition in the technology market makes enterprises face stronger pressure of technological change, so they need to maintain a high and stable level of innovation input and output [37]. Therefore, the operational efficiency of high-tech enterprises is highly dependent on innovation performance.

Based on the above analysis, hypothesis H3b was proposed:

H3b. *Innovation plight inhibits the operation efficiency of enterprises, which is more obvious for enterprises belonging to high-tech industries.*

China has a vast territory, and different regions have different development conditions. Among them, the central and western regions and the eastern regions are always divided into two groups for comparison. Therefore, this paper analyzes and validates the heterogeneity of the core conclusion in the central and western regions and the eastern regions. Combined with hypothesis H3b and the previous discussion on the distribution of innovation plight in the introduction, if the innovation plight faced by high-tech enterprises has a stronger inhibitory effect on operational efficiency, then in the eastern region with a relatively high proportion of high-tech enterprises [38,39], the operational efficiency of enterprises will be more significantly affected by innovation plight.

Based on the above analysis, hypothesis H3c was proposed:

H3c. *The innovation plight of enterprises located in the eastern region has a significant inhibitory effect on operational efficiency.*

3. Research Methodology

3.1. Data Sources

The basic data of variables in this paper come from the annual reports of listed enterprises; the period for building the basic database is 2011–2020. Specifically, the enterprise-level data in this paper come from the China Stock Market & Accounting Research Database (CSMAR), the regional macro-level basic data are obtained from the China Statistical Yearbook, and the basic data of innovation plight come from the patent information disclosed by the China Research Data Service Platform (CNRDS).

To ensure the accuracy of the empirical analysis, we have processed the data as follows. The companies marked with *ST, ST, and PT were removed from the database. In particular, ST is the abbreviation for special treatment, which is marked by the Stock Exchange to issue a warning if a listed company's financial or other conditions are abnormal. *ST means that there is a more serious abnormality in the financial or other conditions of a listed company. PT is used to mark the delisted stocks.

After removing the observed values of ST, *ST, and PT enterprises in the sample period and the samples with missing main research variables from the original data, this paper finally obtained 12,781 unbalanced panel data from 2347 listed enterprises in China's A-share manufacturing industry.

3.2. Model Construction

In order to test the relationship between innovation plight and the operational efficiency of manufacturing enterprises, this paper sets the following two-way fixed effects model:

$$ROA_{i,t} = \alpha_0 + \alpha_1 IDLM_{i,t-1} + \alpha_2 Control_{i,t} + \mu_i + v_t + \varepsilon_{i,t} \quad (1)$$

In the equation, $ROA_{i,t}$ represents the operational efficiency of the listed company i in year t . The $IDLM_{i,t-1}$ represents the degree of innovation plight of the listed company i in year $t - 1$. α_0 represents the intercept term. $Control_{i,t}$ represents the set of control variables. μ_i represents individual fixed effects and v_t represents time-fixed effects. $\varepsilon_{i,t}$ represents the random disturbance term. α_1 represents the average causal effect of the enterprises' innovation plight on their operational efficiency. If α_1 is greater than 0, it indicates that the innovation plight has an incentive effect on the operation efficiency. Conversely, if α_1 is less than 0, it suggests that the innovation plight faced by enterprises inhibits their operational efficiency.

Based on theoretical analysis, this paper holds that innovation plight affects the operational efficiency of manufacturing enterprises through risk-taking capacity, development ability expectation, and profitability. In order to further test the three paths, Model (2) and Model (3) are set as follows based on Model (1):

$$M_{i,t} = \beta_0 + \beta_1 IDLM_{i,t-1} + \beta_2 Control_{i,t} + \mu_i + v_t + \varepsilon_{i,t} \quad (2)$$

$$ROA_{i,t} = \gamma_0 + \gamma_1 IDLM_{i,t-1} + \gamma_2 M_{i,t} + \gamma_3 Control_{i,t} + \mu_i + v_t + \varepsilon_{i,t} \quad (3)$$

In Model (2) and Model (3), $M_{i,t}$ include risk-taking capacity (*SOL*), development capability expectation (*DCE*), and profitability (*PR*). Control variables are consistent with Model (1). The main focus here is on the coefficients β_1 , γ_1 and γ_2 . If the coefficients β_1 of Model (2) and γ_1 and γ_2 of Model (3) are significant; they indicate that technological innovation affects the operational efficiency of enterprises through three paths: risk-taking capacity, development ability expectation, and profitability.

3.3. Variables

3.3.1. Explained Variable

The explained variable of this paper is the operational efficiency (*ROA*), and the return on total assets is selected as its measurement index. The rate of return on total assets is the ratio between the total compensation and the average total assets of an enterprise in a certain period, which is an important index to evaluate the operational efficiency of an enterprise.

3.3.2. Explanatory Variable

The core explanatory variable of this paper is enterprises' innovation plight (*IDLM*). The specific calculation steps are shown in the Figure 1. When measuring the innovation plight of enterprises, this article refers to the three-step calculation method of "determining performance indicators—constructing performance expectations—finding the performance expectation gap" [18] and takes the difference between the actual innovation performance of enterprises (*AIP*) and innovation performance expectation (*EIP*) as the indicator to measure the extent to which an enterprise is in innovation plight.

3.3.3. Control Variables

The control variables selected in this paper are as follows. Enterprise size (*SIZE*): natural logarithm of enterprise operating income; enterprise age (*AGE*): the natural logarithm of the difference between the year observed and the year of establishment of the enterprise; asset-liability ratio (*LEV*): the ratio of corporate liabilities to assets; asset turnover ratio (*ATR*): the ratio of operating income to average total assets; ownership concentration (*CON*): the Herfindahl index of shares held by the top five shareholders of a company; ratio of independent directors (*ID*): the ratio of independent directors to the total number of directors; degree of industry competition (*HHI*): the Herfindahl index of the ratio of a company's operating revenue to its industry.

3.3.4. Instrumental Variable

This article adopts the entropy weight method (*EWM*) to calculate the score of enterprise innovation capability as an instrumental variable (*IV*), referring to the innovation capability evaluation index system conducted by Jiang [40]. The specific index composition of the instrumental variable is shown in Section 4.3.1, endogeneity test, where details of the instrumental variable are introduced.

3.3.5. The Explanatory Variables in Mechanism Analysis

The explanatory variables selected in the mechanism analysis of this paper include risk-taking capacity (*SOL*), development ability expectation (*DCE*), and profitability (*PR*).

Among them, the index of risk-taking ability (*SOL*) is the ratio of profit before interest, tax, depreciation, and amortization to the average balance of liabilities, which reflects the long-term solvency of enterprises and is also an important indicator to examine the risk tolerance of enterprises. The higher the value of this index, the stronger the enterprise's risk-bearing ability.

The expectation of development ability (*DCE*) is measured by the rate of capital preservation and appreciation, which is the ratio of the total value of owners' equity at the end of the current period to the initial value of the current period. This index reflects the preservation and growth of the capital invested by investors. The higher index value

indicates the better capital preservation status of the enterprise, the more secure debt of creditors, and the stronger momentum of enterprise development.

The index of profitability (*PR*) is the profit margin before interest and tax, which is often used by financial management as an important indicator for analyzing a company's profitability. The larger value of the indicator shows the enterprise has more ideal profitability.

The main variables mentioned above and their calculation methods are shown in Table 1.

Table 1. Main variable definitions.

	Variable	Symbol	Calculation Method
Explained variable	Enterprises' operational efficiency	<i>ROA</i>	The ratio of net profit to total assets
Explanatory variable	Enterprises' Innovation plight	<i>IDL</i>	Please refer to Figure 1 in the text for details
Control variables	Enterprises' age	<i>AGE</i>	The natural logarithm of the difference between the year of observation and the year of establishment of the enterprise
	Enterprises' size	<i>SIZE</i>	The natural logarithm of a company's operating income
	Asset liability ratio	<i>LEV</i>	The ratio of total liabilities to total assets
	Asset turnover	<i>ATR</i>	The ratio of total revenue to total assets
	Ownership concentration	<i>CON</i>	The Herfindahl Index of the shareholding proportion of the top five shareholders of the enterprise
	Proportion of independent directors	<i>ID</i>	The ratio of independent directors to the total number of directors on the board of directors
	The level of competition among enterprises in the industry	<i>HHI</i>	The Herfindahl Index of the ratio of a company's operating revenue to its industry
Regional macro variables	Regional GDP	<i>GDP</i>	The natural logarithm of regional GDP
	The proportion of the secondary industry	<i>SIR</i>	The ratio of the output value of the regional secondary industry to the regional GDP

4. Results

4.1. Descriptive Statistics

The descriptive statistics of the main variables in this paper are shown in Table 2. The average operational efficiency (*ROA*) of the samples is 0.037, and the standard deviation is 0.064. The large gap between the maximum value and the minimum value of the operational efficiency reflects the significant difference between the operational efficiency of different companies. And the minimum value is negative, indicating that the operation of some enterprises is not optimistic.

Table 2. Descriptive statistics.

Variable	N	Mean	Min	Median	Max	Sd
ROA	12,781	0.037	−1.220	0.037	0.206	0.064
IDL	12,781	3.029	0	2.289	12.889	3.026
SIZE	12,781	21.442	19.007	21.325	24.320	1.264
AGE	12,781	2.241	0.693	2.303	3.466	0.697
LEV	12,781	0.407	0.053	0.396	1.270	0.195
ATR	12,780	0.631	0.001	0.554	7.609	0.406
CON	12,781	0.151	0.014	0.125	0.563	0.103
ID	12,781	0.376	0.182	0.333	0.800	0.055
HHI	12,781	0.079	0.015	0.065	1	0.062

The standard deviation of enterprise innovation plight (*IDLM*) is 3.026. Among the control variables, the standard deviation of enterprise size (*SIZE*) is 1.264. The number indicates a significant difference in the size of different listed companies in the sample.

To avoid multicollinearity issues between explanatory variables, a variance inflation factor (VIF) test was conducted. The test results are shown in Table 3. The VIF values of all variables are less than 5, indicating there is no problem of estimation distortion caused by multicollinearity in the model.

Table 3. Variance inflation factor (VIF) test.

Variable	VIF	1/VIF
IDLM	1.07	0.938
SIZE	1.88	0.531
AGE	1.39	0.717
LEV	1.34	0.744
ATR	1.29	0.778
CON	1.12	0.894
ID	1.01	0.988
HHI	1.03	0.974

4.2. Baseline Regression Results

Table 4 shows the results of baseline regression for Model (1). In this paper, a stepwise regression method is adopted. Year-fixed effect and province-fixed effect are gradually added column by column. According to column (1)–(3) of Table 4, the regression coefficients of innovation plight on enterprise operational efficiency are all negative, and all pass the significance test at 1% level. The results show that Model (1) has a good fitting effect. After considering the influence of time and region, the regression coefficient of innovation plight on operational efficiency is negative at the significance level of 1%.

Table 4. Impact of innovation plight on operational efficiency.

Variable	(1)	(2)	(3)
	ROA	ROA	ROA
IDLM	−0.0009 *** (0.0002)	−0.0008 *** (0.0002)	−0.0008 *** (0.0002)
SIZE	0.0190 *** (0.0005)	0.0192 *** (0.0005)	0.0191 *** (0.0005)
AGE	−0.0173 *** (0.0008)	−0.0174 *** (0.0008)	−0.0169 *** (0.0008)
LEV	−0.1680 *** (0.0028)	−0.1691 *** (0.0028)	−0.1680 *** (0.0029)
ATR	0.0103 *** (0.0013)	0.0098 *** (0.0013)	0.0095 *** (0.0013)
CON	0.0266 *** (0.0048)	0.0264 *** (0.0048)	0.0272 *** (0.0049)
ID	−0.0346 *** (0.0087)	−0.0325 *** (0.0087)	−0.0320 *** (0.0087)
HHI	−0.0333 *** (0.0077)	−0.0319 *** (0.0077)	−0.0316 *** (0.0078)
Constant	−0.2560 *** (0.0103)	−0.2595 *** (0.0103)	−0.2589 *** (0.0104)
Year FE	NO	YES	YES
Province FE	NO	NO	YES
N	12,780	12,780	12,780
R ²	0.3026	0.3063	0.3113

Notes: Standard errors in parentheses. The symbols *** represent the levels of significance at the 1% levels. This note applies to the following Tables.

The above results show that innovation plight has a significant negative effect on the operational efficiency of manufacturing enterprises. Hypothesis H1 is verified and considered to be valid.

4.3. Robustness Test

4.3.1. Instrumental Variable Method

In reality, many potential factors affect the operational efficiency of enterprises, so there are problems that may cause endogeneity. Therefore, this paper further uses the instrumental variable method to re-estimate.

After multiple tests, we chose innovation capability (IV) as the instrumental variable. Here is the reason. Theoretically, innovation capability is likely to have a strong correlation with the innovation plight of enterprises, which satisfies the first condition of being an instrumental variable. And the result of the empirical test in Section 4.2 also confirms the existence of this relation. It shows that the innovation capability (IV) of enterprises is correlated with the innovation plight at the significance level of 1%, and the Cragg-Donald Wald F statistic is greater than 16.38, which indicates that the innovation capability (IV) passes the weak instrumental variable test.

How, then, do we meet the exogenous condition? It should be proved that innovation capability can only affect operational efficiency through innovation plight. However, econometric methods cannot be used for testing the exogeneity of instrumental variables. As the number of instrumental variables equals the number of endogenous explanatory variables, which is a “perfect identification”, we can only conduct qualitative discussions or rely on expert opinions.

Referring to the innovation capability index system conducted by Jiang [40], this article adopts the entropy weight method (EWM) to calculate the score of enterprises’ innovation capability as an instrumental variable. The modified index system is shown in Table 5.

Table 5. Evaluation index system for innovation capability of firms (IV).

Primary Indicators	Secondary Indicators
Innovation Investment Capacity X1	The proportion of technical personnel to the total number of employees X11
	Research and development expense ratio X12
Innovation Management Capacity X2	The proportion of administrative staff to the total number of employees X21
	Management expense rate X22
Innovation Marketing Capacity X3	The proportion of sales staff to the total number of employees X31
	Sales expense rate X32
Innovation Output Capacity X4	Per capita number of invention patent applications authorized X41
	The growth rate of revenue X42

Theoretically, innovation capability (IV) is just an objective evaluation based on the information of the enterprise in Table 5. So innovation capability can only affect the operation of the enterprise after being transformed into innovative achievements. Reasonably, the transformation of innovative achievements determines the innovation situation of enterprises, which further affects their operational efficiency. Therefore, innovation capability is theoretically exogenous. In other words, the lower the innovation capability of an enterprise, the more possible innovation plight it will face, and according to the core conclusion, the lower the operational efficiency of the enterprise is.

After considering the endogenous problems, we re-estimate the impact of innovation plight on operational efficiency. Column (2) of Table 6 shows that the regression coefficient

of the impact of enterprise innovation plight on operational efficiency is still negative at the significance level of 1%. Therefore, the core conclusion (Hypothesis 1) of this paper is still valid.

Table 6. Robustness test regression results 1.

Variable	(1)	(2)	(3)	(4)
	IDLM	ROA	ATR	ROA
IV	−6.2854 *** (0.8902)			
IDLM		−0.0096 *** (0.0030)	−0.0099 *** (0.0011)	−0.0008 *** (0.0002)
SIZE	0.0323 (0.0274)	0.0193 *** (0.0006)	0.1664 *** (0.0031)	0.0191 *** (0.0005)
AGE	1.0735 *** (0.0433)	−0.0075 ** (0.0033)	−0.0439 *** (0.0056)	−0.0169 *** (0.0008)
LEV	0.6058 *** (0.1503)	−0.1613 *** (0.0039)	−0.1759 *** (0.0188)	−0.1682 *** (0.0029)
ATR	−0.6556 *** (0.0699)	0.0051 ** (0.0024)		0.0095 *** (0.0013)
CON	−1.1449 *** (0.2545)	0.0169 *** (0.0064)	−0.0252 (0.0322)	0.0273 *** (0.0049)
ID	0.7924 * (0.4556)	−0.0246 ** (0.0099)	−0.1425 ** (0.0577)	−0.0319 *** (0.0087)
HHI	−1.6801 *** (0.4101)	−0.0432 *** (0.0094)	0.3438 *** (0.0513)	−0.0316 *** (0.0078)
GDP				0.0158 ** (0.0068)
SIR				0.0001 (0.0002)
Constant	0.3148 (0.5521)		−2.7071 *** (0.0646)	−0.4327 *** (0.0728)
Year FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Cragg-Donald Wald F statistic	49.857			
Observations	12,781	12,781	12,781	12,770
R ²	0.1648	0.1386	0.2607	0.3118

Notes: Standard errors in parentheses. The symbols *, **, and *** represent the levels of significance at the 10%, 5%, and 1% levels, respectively.

4.3.2. Replace the Dependent Variable

In addition to the return on assets (ROA) mentioned earlier, there are many other indicators for evaluating the operational efficiency of enterprises. Therefore, in order to test the robustness of the core conclusion, this article replaces the dependent variable with the total asset turnover rate (ATR). It is an important indicator for evaluating the operational quality of a company, measured by the ratio of total revenue to total assets. The higher the total asset turnover rate a company receives, the faster the asset turnover speed of the enterprise is, and the higher the level of enterprise management is.

After replacing the dependent variable, the basic regression results of Model 1 are displayed in column (3) of Table 6. The regression coefficient of innovation plight (IDLM) on the total asset turnover rate (ATR) is negative and passes the significance test at a 1% level, which shows that the innovation plight still has a significant inhibitory effect on operational efficiency after changing the indicator of operational efficiency.

4.3.3. Add Regional Macro Variables

The operational efficiency of enterprises is not only affected by the enterprise level, but also by the macro-factors, such as economic development and industrial structure adjustment at the regional level. Therefore, this paper further controls the level of economic

growth (*GDP*) and industrial structure (*SIR*) at the regional level to reduce the endogenous problems caused by missing variables. The results in column (4) of Table 6 show that the regression coefficient of innovation plight on economic efficiency is still negative at the significance level of 1% after adding the control variables at the regional macro level. This shows that the core conclusion of this paper is still sound.

4.3.4. Replace the Parameters of the Core Explanatory Variable for Measurement

This paper further tests the robustness of the model by changing the value of the parameter used in the measurement of innovation performance expectation (EIP). In the original data of the innovation plight, the value of parameter β is 0.5. For further robustness tests, the value of the parameter is changed to 0.4 and 0.6, respectively. The results are shown in columns (1) and (2) of Table 7, and the regression coefficients of innovation plight are both significantly negative. After changing the value of the β parameter, the inhibitory effect of innovation plight on operational efficiency is still significant, and the core conclusion of this paper is robust.

Table 7. Robustness test regression results 2.

Variable	(1)	(2)	(3)	(4)
	ROA	ROA	ROA	ROA
IDLM			−0.0011 *** (0.0002)	
IDLM_4	−0.0008 *** (0.0002)			
IDLM_6		−0.0008 *** (0.0002)		
L.IDLM				−0.0008 *** (0.0002)
SIZE	0.0191 *** (0.0005)	0.0191 *** (0.0005)	0.0183 *** (0.0006)	0.0197 *** (0.0006)
AGE	−0.0169 *** (0.0009)	−0.0170 *** (0.0008)	−0.0160 *** (0.0009)	−0.0173 *** (0.0011)
LEV	−0.1681 *** (0.0029)	−0.1680 *** (0.0029)	−0.1607 *** (0.0032)	−0.1720 *** (0.0034)
ATR	0.0095 *** (0.0013)	0.0095 *** (0.0013)	0.0077 *** (0.0014)	0.0100 *** (0.0016)
CON	0.0273 *** (0.0049)	0.0274 *** (0.0049)	0.0182 *** (0.0055)	0.0311 *** (0.0058)
ID	−0.0320 *** (0.0087)	−0.0321 *** (0.0087)	−0.0379 *** (0.0099)	−0.0319 *** (0.0102)
HHI	−0.0319 *** (0.0078)	−0.0318 *** (0.0078)	−0.0295 *** (0.0086)	−0.0392 *** (0.0093)
Constant	−0.2588 *** (0.0104)	−0.2585 *** (0.0104)	−0.2410 *** (0.0118)	−0.2708 *** (0.0123)
Year FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
N	12,780	12,780	9190	9775
R ²	0.3112	0.3111	0.3265	0.2946

Notes: Standard errors in parentheses. The symbols *** represent the levels of significance at the 1% levels.

4.3.5. Replace the Time Interval of the Sample

The original time interval of the sample is 2011–2020, and the paper further revised the interval of sample time to 2011–2018. The robustness results are shown in Column (3) of Table 7, and the regression coefficient of innovation plight is also negative at the significance level of 1%. The results show that the core conclusion of this paper is still valid.

4.3.6. Lag the Core Explanatory Variable

In this robustness test, the core explanatory variable innovation plight (*IDLM*) is re-estimated with a one-stage lag, and the estimated results are shown in Column (4) of Table 7. It can be seen from the results that the regression coefficient of innovation plight lag one stage (*L.IDLM*) is negative at the significance level of 1%. The core conclusions of this paper remain sound.

4.4. Mechanism Analysis

4.4.1. Risk-Taking Capacity

Based on the theoretical analysis in Section 2, risk-bearing capacity (*SOL*) is one of the pathways through which innovation plight affects operational efficiency. In particular, this article chooses the ratio of EBITDA (earnings before interest, taxes, depreciation, and amortization) to the average balance of liability as an indicator of risk-bearing capacity. Because it can reflect the long-term solvency of enterprises and is also an important indicator to examine the risk-bearing capacity of enterprises. The higher the value of this ratio, the stronger the enterprise's risk-bearing ability is.

Columns (1)–(3) of Table 8 show the results of the mechanism test for risk-bearing capacity.

Table 8. Analysis of the mechanism of action 1.

Variable	Risk Bearing Capacity			Development Capacity Expectation		
	(1)	(2)	(3)	(4)	(5)	(6)
	SOL	ROA	ROA	DCE	ROA	ROA
IDLM	−0.0083 *** (0.0011)		−0.0002 (0.0001)	−0.0062 ** (0.0030)		−0.0008 *** (0.0002)
SOL		0.0789 *** (0.0011)	0.0788 *** (0.0011)			
DCE					0.0064 *** (0.0005)	0.0063 *** (0.0005)
SIZE	0.0567 *** (0.0034)	0.0144 *** (0.0005)	0.0144 *** (0.0005)	0.0830 *** (0.0093)	0.0184 *** (0.0005)	0.0185 *** (0.0005)
AGE	−0.0766 *** (0.0056)	−0.0110 *** (0.0007)	−0.0109 *** (0.0007)	−0.1611 *** (0.0151)	−0.0168 *** (0.0008)	−0.0159 *** (0.0008)
LEV	−1.2640 *** (0.0188)	−0.0682 *** (0.0028)	−0.0682 *** (0.0028)	−0.4533 *** (0.0510)	−0.1655 *** (0.0029)	−0.1649 *** (0.0029)
ATR	0.0214 ** (0.0088)	0.0089 *** (0.0011)	0.0088 *** (0.0011)	−0.1284 *** (0.0239)	0.0112 *** (0.0013)	0.0107 *** (0.0013)
CON	0.1611 *** (0.0321)	0.0148 *** (0.0042)	0.0146 *** (0.0042)	−0.3472 *** (0.0865)	0.0302 *** (0.0048)	0.0293 *** (0.0048)
ID	−0.1339 ** (0.0575)	−0.0217 *** (0.0074)	−0.0215 *** (0.0075)	−0.0828 (0.1549)	−0.0322 *** (0.0087)	−0.0315 *** (0.0087)
HHI	−0.3171 *** (0.0513)	−0.0069 (0.0066)	−0.0071 (0.0066)	−0.2119 (0.1380)	−0.0294 *** (0.0077)	−0.0304 *** (0.0077)
Constant	−0.1475 ** (0.0687)	−0.2442 *** (0.0089)	−0.2443 *** (0.0089)	0.1607 (0.1856)	−0.2583 *** (0.0104)	−0.2586 *** (0.0104)
Sobel Z		−8.695 ***			−3.524 ***	
Bootstrap [95% confi.interval] (ind_eff)		[−0.0009, −0.0006]			[−0.0001, −0.0000]	
Year FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
N	12,781	12,781	12,781	12,772	12,772	12,772
R ²	0.3409	0.4980	0.4981	0.0397	0.3179	0.3191

Notes: Standard errors in parentheses. The symbols ** and *** represent the levels of significance at the 5%, and 1% levels, respectively.

The results show that the regression coefficient of innovation plight (*IDLM*) in Column (1) is significantly negative at the level of 1%, indicating that innovation plight has a significant negative impact on the risk-bearing capacity (*SOL*) of enterprises.

In Column (2), the regression coefficient of risk-bearing capacity (*SOL*) is significantly positive at the level of 1%, indicating that risk-bearing capacity has a significant positive effect on operational efficiency (*ROA*).

Column (3) shows the regression results of Model (3) to test whether enterprise risk-bearing capacity can be used as a path. The results show that after adding risk-bearing capacity, the significance of innovation plight on the regression coefficient of enterprise operational efficiency (*ROA*) decreases significantly compared with baseline regression. What is more, the absolute value of the coefficient decreases, which is smaller than the coefficient in baseline regression in Column (3) of Table 4. And the regression coefficient of risk-bearing ability (*SOL*) on operational efficiency (*ROA*) is still significantly positive. The results above indicate that the addition of risk-bearing ability weakens the impact of innovation plight on operational efficiency.

In addition, the risk-bearing capacity mechanism passed the Sobel test and the Bootstrap test. In detail, Table 8 expresses that the Z-value obtained by the Sobel test is significant with three stars, while the confidence interval of indirect effect obtained by the Bootstrap test does not contain a 0 value. The above test results indicate that risk-bearing capacity passes the mechanism test; that is, innovation plight inhibits the operational efficiency of manufacturing enterprises through risk-bearing capacity (*SOL*).

In conclusion, the hypothesis H2a is verified.

4.4.2. Development Capacity Expectation

In the theoretical analysis in Section 2, it is mentioned that the innovation plight can also inhibit the operational efficiency of enterprises through the development capability expectation (*DCE*) of enterprises. The indicator of expected development ability is the rate of capital preservation and appreciation, which is the ratio of the total owners' equity at the end of the current period to the beginning of the current period. The ratio reflects the preservation and growth of the capital invested by investors. A higher value indicates that the capital preservation status of the enterprise is better.

Columns (4)–(6) of Table 8 show the results of the mechanism test for developmental capability expectation (*DCE*).

Column (4) of Table 8 shows that the regression coefficient of innovation plight (*IDLM*) on development capability expectation in Column (4) is significantly negative at the level of 5%. It indicates that innovation plight has a significant negative impact on the developmental capacity expectation (*DCE*).

In Column (5), the regression coefficient of development capacity expectation (*DCE*) on operational efficiency (*ROA*) is significantly positive at the level of 1%. It expresses that development capacity expectation has a significant positive effect on operational efficiency (*ROA*).

Column (6) shows the regression results of Model (3) to test whether developmental capacity expectation (*DCE*) can be used as a path. The results show that after adding developmental capacity expectation, the significance of the regression coefficient of innovation plight (*IDLM*) decreases significantly compared to the baseline regression. Also, the absolute value of the coefficient decreases, which is smaller than the coefficient in baseline regression in Column (3) of Table 4. And the regression coefficient of developmental capacity expectation on operational efficiency (*ROA*) is still significantly positive, indicating that the addition of developmental capacity expectation weakens the impact of innovation plight on operational efficiency.

In addition, the development capacity expectation (*DCE*) also passed the Sobel test and the Bootstrap test. In detail, Table 8 indicates that the Z-value obtained by the Sobel test is significant with three stars, while the confidence interval of indirect effect obtained by the Bootstrap test does not contain a 0 value. The above test results indicate that development

capacity expectation passes the mechanism test. The developmental capacity expectation is one of the paths through which innovation plight inhibits enterprises' operational efficiency.

In conclusion, hypothesis H2b is verified.

4.4.3. Profitability

From the theoretical analysis in Section 2, the innovation plight faced by manufacturing enterprises will also have a negative effect on operational efficiency by inhibiting the enterprise's profitability (*PR*). The indicator of profitability is the profit margin before interest and tax, which can reflect the situation of earnings of the enterprise. The larger the value of this indicator is, the better enterprises' profitability is.

Columns (1)–(3) of Table 9 show the results of the mechanism test for profitability (*PR*).

Column (1) shows that the regression coefficient of innovation plight (*IDL*M) on profitability is significantly negative at the level of 5%.

Column (2) expresses that the regression coefficient of profitability on operational efficiency (*ROA*) is significantly positive at a 1% level.

Column (3) shows that the absolute value of the regression coefficient of innovation plight on operational efficiency decreases after the addition of profitability, which is smaller than the coefficient in baseline regression in Column (3) of Table 4. It indicates that the addition of profitability weakens the impact of innovation plight on business efficiency.

Table 9. Analysis of the mechanism of action 2.

Variable	Profitability		
	(1)	(2)	(3)
	PR	ROA	ROA
IDL	−0.0025 ** (0.0013)		−0.0007 *** (0.0002)
PR		0.0539 *** (0.0011)	0.0538 *** (0.0011)
SIZE	0.0589 *** (0.0039)	0.0157 *** (0.0005)	0.0157 *** (0.0005)
AGE	−0.0439 *** (0.0063)	−0.0153 *** (0.0008)	−0.0145 *** (0.0008)
LEV	−0.4137 *** (0.0211)	−0.1461 *** (0.0027)	−0.1456 *** (0.0027)
ATR	−0.0497 *** (0.0099)	0.0136 *** (0.0012)	0.0132 *** (0.0012)
CON	0.0049 (0.0361)	0.0278 *** (0.0045)	0.0270 *** (0.0045)
ID	−0.1660 ** (0.0646)	−0.0237 *** (0.0080)	−0.0232 *** (0.0080)
HHI	−0.1675 *** (0.0576)	−0.0222 *** (0.0071)	−0.0231 *** (0.0071)
Constant	−0.8012 *** (0.0772)	−0.2125 *** (0.0096)	−0.2128 *** (0.0096)
Sobel Z		−3.557 ***	
Bootstrap [95% confi.interval] (ind_eff)		[−0.0004, −0.0000]	
Year FE	YES	YES	YES
Province FE	YES	YES	YES
N	12,781	12,781	12,781
R ²	0.0494	0.4204	0.4213

Notes: Standard errors in parentheses. The symbols **, and *** represent the levels of significance at the 5%, and 1% levels, respectively.

In addition, the profitability has also passed the Sobel test and Bootstrap test. In detail, Table 9 shows that the Z-value obtained by the Sobel test is significant with three stars, while the confidence interval of indirect effect obtained by the Bootstrap test does not contain a 0 value. The above test results indicate that profitability passes the mechanism test. It is one of the paths through which innovation plight inhibits enterprises' operational efficiency.

In conclusion, the hypothesis H2c in this paper is verified.

4.5. The Heterogeneity Analysis

4.5.1. Firm-Level Heterogeneity Analysis

1. State-owned Enterprises and Non State-owned Enterprises

As for the different ownership structures of enterprises, the innovation plight has different levels of negative impact on the operational efficiency of enterprises.

Comparing Columns (1) and (2) in Table 10, there is a significant difference between the regression coefficients of state-owned enterprises and non-state-owned enterprises. In detail, the regression coefficient of non-state-owned enterprises is negative at the significance level of 1%, while the regression coefficient of state-owned enterprises is not significant.

In conclusion, the regression results from Columns (1)–(2) of Table 10 verified hypothesis H3a about the heterogeneity of the ownership structure of enterprises.

Table 10. Firm-level heterogeneity.

Variable	Ownership Structure		Firm Size		Life Cycle			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	State-Owned	Non-State-Owned	Large Scale	Small and Medium Size	Start-Up Period	Growth Period	Mature Period	Recession Period
IDLM	−0.0001 (−0.45)	−0.0011 *** (−5.40)	−0.0002 (−1.11)	−0.0011 *** (−4.13)	−0.0008 (0.0005)	−0.0008 *** (0.0002)	−0.0007 (0.0006)	−0.0022 * (0.0013)
SIZE	0.0168 *** (19.70)	0.0204 *** (30.75)	0.0160 *** (18.79)	0.0178 *** (13.51)	0.0179 *** (0.0016)	0.0141 *** (0.0007)	0.0169 *** (0.0018)	0.0140 *** (0.0041)
AGE	−0.0089 *** (−4.52)	−0.0179 *** (−16.79)	−0.0107 *** (−9.30)	−0.0214 *** (−16.94)	−0.0193 *** (0.0027)	−0.0186 *** (0.0011)	−0.0086 *** (0.0032)	−0.0040 (0.0073)
LEV	−0.1770 *** (−36.83)	−0.1610 *** (−45.20)	−0.1855 *** (−48.84)	−0.1531 *** (−36.21)	−0.1416 *** (0.0093)	−0.1300 *** (0.0041)	−0.1774 *** (0.0095)	−0.1277 *** (0.0195)
ATR	0.0068 *** (2.89)	0.0112 *** (6.90)	0.0035 ** (2.56)	0.0381 *** (12.06)	0.0094 ** (0.0037)	0.0092 *** (0.0020)	0.0078 * (0.0044)	0.0196 ** (0.0091)
CON	0.0034 (0.42)	0.0478 *** (7.75)	0.0299 *** (5.22)	0.0285 *** (3.40)	0.0027 (0.0172)	0.0141 ** (0.0061)	0.0855 *** (0.0178)	0.0657 (0.0436)
ID	−0.0571 *** (−3.75)	−0.0208 * (−1.95)	−0.0358 *** (−3.18)	−0.0238 * (−1.80)	−0.0321 (0.0289)	−0.0067 (0.0109)	−0.0766 ** (0.0303)	−0.0776 (0.0672)
HHI	−0.0045 (−0.35)	−0.0486 *** (−5.02)	−0.0221 ** (−2.28)	−0.0327 *** (−2.68)	0.0091 (0.0242)	−0.0387 *** (0.0094)	−0.0453 * (0.0267)	−0.0586 (0.0677)
Constant	−0.2181 *** (−12.69)	−0.2933 *** (−21.66)	−0.1938 *** (−11.00)	−0.2456 *** (−9.19)	−0.2530 *** (0.0330)	−0.1655 *** (0.0138)	−0.2204 *** (0.0375)	−0.2043 ** (0.0828)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES	YES
N	3699	9082	6390	6391	1442	4457	1283	315
R ²	0.3392	0.3060	0.3384	0.3170	0.2780	0.3389	0.3296	0.3420

Notes: t statistics in parentheses ***, **, and * indicate significance at the 1%, 5%, and 10% statistical levels, respectively.

2. Large Scale Enterprises and Small and Medium-scale Enterprises

At the enterprise level, the heterogeneity of firm scale is also analyzed. The enterprises in the sample are divided into small and medium-sized enterprises and large enterprises by using the natural logarithm of operating income. The regression coefficients of the two types of enterprises' operational efficiency (ROA) affected by innovation plight (IDL) are shown in columns (3)–(4) of Table 10. In general, the innovation plight has a negative effect on the operational efficiency of the two types of enterprises. The specific comparison shows that the regression coefficient of large enterprises is not significant and greatly different from that of small and medium-sized enterprises, while the regression coefficient of small and medium-sized enterprises is negative at the significance level of 1%, and the absolute value of the coefficient is larger.

In conclusion, the regression results from Columns (3)–(4) of Table 10 verified hypothesis H3b about the heterogeneity of the scale of enterprises.

3. Start-up Period, Growth Period, Mature Period, and Recession Period

In addition to the ownership structure and scale of enterprises, the different life cycles of enterprises may also differ in the impact of innovation plight (IDL) on operational efficiency (ROA). Based on the experience of Dickinson [35], this paper divides the life cycle of an enterprise into the start-up stage, growth stage, maturity stage, and decline stage according to the cash flow data. As shown in Columns (5)–(8) in Table 10, the innovation plight faced by enterprises in the growth period or the development period has the most significant negative effect on operational efficiency, which passes the significance test of 1%. The second is the enterprises in the recession period, whose regression coefficient is negative at the significance level of 10%. However, for enterprises in the initial and mature stages, the negative effect of innovation plight on operational efficiency is not significant.

In conclusion, the regression results from Columns (5)–(8) of Table 10 verified hypothesis H3b about the heterogeneity of the life cycle scale of enterprises.

4.5.2. Industry-Level Heterogeneity

According to the type of manufacturing industry, enterprises can be divided into high-tech enterprises and non-high-tech enterprises. Columns (1)–(2) of Table 11 show that the regression coefficients of innovation plight (IDL) between high-tech enterprises and non-high-tech enterprises differ. In particular, the regression coefficient of high-tech enterprises is significantly negative at the significance level of 1%, while the regression coefficient of non-high-tech enterprises is not significantly positive. The results indicate that compared with non-high-tech enterprises, innovation plight has a more significant impact on the operational efficiency of high-tech enterprises.

In conclusion, the results in Columns (1) and (2) in Table 11 confirm the hypothesis H3b.

Table 11. Industrial and regional heterogeneity.

	Industry-Level		Region-Level	
	(1)	(2)	(3)	(4)
	High-Tech	Non-High-Tech	Central and West	East
IDL	−0.0012 *** (−5.97)	0.0004 (0.99)	−0.0009 ** (−2.49)	−0.0008 *** (−4.29)
SIZE	0.0181 *** (27.79)	0.0189 *** (21.06)	0.0183 *** (18.78)	0.0192 *** (31.04)
AGE	−0.0174 *** (−16.67)	−0.0149 *** (−10.13)	−0.0137 *** (−7.98)	−0.0182 *** (−18.58)
LEV	−0.1693 *** (−48.41)	−0.1636 *** (−33.00)	−0.1749 *** (−32.80)	−0.1643 *** (−48.40)
ATR	0.0279 *** (12.83)	0.0021 (1.24)	0.0079 *** (2.94)	0.0113 *** (7.33)

Table 11. Cont.

	Industry-Level		Region-Level	
	(1)	(2)	(3)	(4)
	High-Tech	Non-High-Tech	Central and West	East
CON	0.0279 *** (4.66)	0.0233 *** (2.75)	0.0233 ** (2.46)	0.0290 *** (5.12)
ID	−0.0359 *** (−3.38)	−0.0135 (−0.88)	−0.0250 (−1.44)	−0.0352 *** (−3.49)
HHI	−0.0361 *** (−3.27)	0.0048 (0.38)	−0.0193 (−1.27)	−0.0378 *** (−4.19)
Constant	−0.2434 *** (−18.90)	−0.2718 *** (−14.89)	−0.2495 *** (−12.74)	−0.2606 *** (−21.13)
Observations	8813	3968	3622	9159
R-squared	0.3291	0.3219	0.3220	0.3054
Year FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES

Notes: t statistics in parentheses. ***, and ** indicate significance at the 1%, and 5% statistical levels, respectively.

4.5.3. Regional Heterogeneity

According to the different regions of the enterprises, the enterprises in the sample are divided into enterprises in the central and western regions and enterprises in the eastern region. Columns (3)–(4) of Table 11 show that the innovation plight of enterprises (*IDLM*) in different regions has a negative impact on business efficiency (*ROA*). In detail, the enterprises located in the eastern region passed the significance test at the 1% level, while the central and western regions passed the significance test at the 5% level. In contrast, the innovation plight has a more serious impact on the operational efficiency of enterprises located in the eastern region.

In conclusion, the results in Columns (3) and (4) in Table 11 confirm the hypothesis H3c.

5. Conclusions and Discussion

5.1. Conclusions

In recent years, in the context of the continuous fierce competition in technological innovation, the complexity of the global technological innovation environment has been increasing. The manufacturing industry in China is highly impacted. And the innovation situation faced by Chinese manufacturing enterprises has gradually become the focus of attention. The efficiency of enterprise operation is one of the main indicators to measure the operational level of enterprises. Therefore, we study the relationship between these two variables and the mechanism behind it.

This article uses data from Chinese A-share-listed manufacturing enterprises from 2011 to 2020. Based on theoretical analysis, it empirically verifies the negative impact of innovation plight on the operational efficiency of manufacturing enterprises.

More conclusions are as follows. First, innovation plight inhibits operational efficiency through three paths, including reducing enterprises' risk-taking ability, development ability expectations, and profitability. Second, the inhibitory effect of innovation plight on operational efficiency is more pronounced in non-state-owned enterprises, small and medium-sized enterprises, high-tech enterprises, and enterprises in the eastern region.

5.2. Discussion

However, there are several limitations that need to be improved in this article.

First, data limitations. Indicators for measuring the operational efficiency of manufacturing enterprises may need improvement. Currently, a large number of researchers use the DEA method and Tobit model to calculate and evaluate operational efficiency. Future research can improve operational efficiency indicators and use them to study the

impact of technological innovation on manufacturing enterprises. There is also room for improvement in the indicators of innovation plight. Future research can calculate the innovation plight based on data other than innovation output.

Second, there are more topics worth further research based on this article's conclusion. For example, the reasons for the distribution of innovation plight in China can be further discussed. What is more, the measurement of the innovation plight of enterprises, the updating of data. They all can be the objects of future research.

Third, deeper research. The innovation status of enterprises still needs further research in the future. Future research can conduct specific analyses based on regional differences, which can help specific regions address innovation plight in a targeted manner.

To promote the level of technological innovation requires the joint efforts of all sectors of society.

For manufacturing enterprises. First, it is important to avoid falling into innovation plight as much as possible, as the conclusion drawn in this article is that innovation plight has a negative impact on the operational efficiency of enterprises. Second, when manufacturing enterprises discover that they are about to or have already faced innovation plight, they should evaluate their risk bearing ability, development ability, and profitability timely. Based on objective evaluation, determine whether the enterprise should continue to invest in R&D.

For policy makers, targeted support plans should be developed for different manufacturing enterprises. In particular, high-tech enterprises ought to be supported strongly, such as fair talent treatment, more funding investment, and a better business environment. What is more, acceleration in the establishment of the Innovation Industrial Cluster in the central and western regions is conducive to narrowing the gap among regions.

All in all, the construction of balanced and high-quality development of China's manufacturing industry needs long-term planning and sustained efforts.

Author Contributions: Conceptualization, Y.S. and Y.Y.; methodology, Y.S.; software, Y.Y.; validation, Y.S.; formal analysis, Y.S. and Y.Y.; investigation, Y.Y.; resources, Y.S.; data curation, Y.S. and Y.Y.; writing—original draft preparation, Y.Y.; writing—review and editing, Y.S.; visualization, Y.S. and Y.Y.; supervision, Y.S.; project administration, Y.S.; funding acquisition, Y.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Social Science Fund of China (Grant No. 19BJL048). The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflict of interest.

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