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Does Technological Innovation Efficiency Improve the Growth of New Energy Enterprises? Evidence from Listed Companies in China

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Abstract: With the implementation of “carbon peaking and carbon neutrality” in China, new energy enterprises, as the vanguard in this strategy, have entered a new era of innovation-driven development. However, enterprises at different lifecycle stages will face different internal and external conditions, and there are differences in their internal mechanisms and business performance. In this case, whether technological innovation efficiency can have an obviously positive effect on their growth and what different effects it can have for enterprises at different lifecycle stages have become issues of great concern to company management, investors, governments, and other stakeholders. This research takes 81 new Chinese energy enterprises as the research objects. First, they are divided into growing, mature, and declining enterprises based on the cash flow combination method. Then, their technological innovation efficiencies from 2016 to 2021 are calculated based on the stochastic frontier method and their growth evaluations are performed by taking both financial and non-financial indicators into consideration. Finally, by taking mediating effects into consideration, the heterogeneity effects of technological innovation efficiency on their growth are studied from the perspective of enterprise lifecycles based on the fixed-effect model. The research results indicate that the technological innovation efficiency of new Chinese energy enterprises has fluctuated around 0.90 in recent years, and is generally at a high level. The efficiency ranking of enterprises at different lifecycle stages is mature period > growing period > declining period. Technological innovation efficiency has a positive impact on their growth, and market share plays a mediating role in this process. The effects of technological innovation efficiency on enterprises at different stages are different, with growing and mature enterprises showing a positive impact. Growing enterprises are more affected by technological innovation efficiency due to their demand for innovation-driven development, while declining enterprises often face difficulties such as unstable operating conditions and outdated equipment, and unreasonable technological innovations may actually accelerate their decline.

Keywords: lifecycle stages; technological innovation efficiency; growth level; new energy; listed companies



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1. Introduction

As China’s economy enters the stage of high-quality development, an innovative economy and a green economy have become the main themes [1]. The Fifth Plenary Session of the 19th Central Committee of the Communist Party of China (CPC) clearly proposed accelerating the development of new energy industries, promoting the innovation of new energy technology, and promoting the popularization and application of new energy products. The proposal of “domestic and international dual circulation” and “carbon peaking and carbon neutrality” has further promoted the development of overseas markets

for new energy enterprises in China. Under the advantages of policy support and market expansion, new Chinese energy enterprises are in an unprecedented period of development opportunities [2].

Building a new, green and low-carbon energy system by developing new energy and reducing traditional fossil energy consumption is an important measure to control greenhouse gas emissions and achieve global carbon neutrality [3]. In energy transition, strengthening the innovation of new energy technologies is an important means to promote their high-quality and efficient utilization [4]. Major countries around the world give priority to energy technology as a breakthrough point in the new technological and industrial revolution [5] and have formulated policies in order to take the leading position in economic development. The United States has issued the Inflation Reduction Act, the European Union has formulated The Renewable Energy Development Act, and Japan has formulated The Energy and Environment Innovation Strategy for 2030. The implementation Plan for Promoting High-Quality Development of New Energy in the New Era, the 14th Five-Year Plan for Renewable Energy Development, and the 14th Five-Year Plan for Modern Energy System, issued by the Chinese National Energy Administration, all stress the need to adhere to innovation-driven development and improve renewable energy utilization. Technological innovation plays a crucial role in reducing new energy costs and improving its efficiency, helping to promote the complementary utilization of diverse new energy sources such as solar, wind, and hydropower and enhancing the resilience and sustainability of the energy system [6]. Meanwhile, new, diversified energy development can also meet the energy needs of different regions and industries and achieve the diversification of energy. Enterprises usually play major roles in the technological innovation of an industry [7].

Compared with developed countries such as the United States and the European Union, new Chinese energy enterprises are moving from the embryonic stage to the growth stage. Enterprise development still depends on backward technology and market subsidies, so it lacks advantages in competition with the traditional energy industry [8]. At present, new Chinese energy enterprises still face significant challenges, such as high costs in power generation and storage and a lack of core technologies, which hinder their growth and development to some extent. To improve their power generation efficiency and to lower costs, technological upgrading and iteration are more important than expanding their scales [9]. However, difficulties, such as advanced technology still being immature, high costs in R&D, and much uncertainty in investment returns, inevitably exist in these enterprises. In this context, these are key problems that new Chinese energy enterprises should overcome urgently, and they must accurately judge how to efficiently utilize manpower, material resources, funds, and relevant policies with the minimal input to achieve the maximum profit and stand out in market competition. Therefore, technological innovation efficiency, as an important driving force, has become a key issue to be addressed in their long-term development [10]. Also, enterprises at different lifecycle stages will face different internal and external conditions, and there are differences in their internal mechanisms and business performance. In this case, whether technological innovation efficiency can have an obviously positive effect on their growth and what different effects it can have for enterprises at different lifecycle stages have become issues of great concern to company management, investors, governments, and other stakeholders [11].

Under the background of “carbon peaking and carbon neutrality”, a new round of technology and energy revolution is about to take place. As the vanguard of high-quality energy development, new energy enterprises featuring new technologies, new business forms, and new models are facing unprecedented opportunities [12]. In this case, studying the impact of technological innovation efficiency is of great significance for China and even the world in the clean, low-carbon, and high-quality energy transition [13] and helps to solve the “impossible triangle” in this industry (accessibility, affordability,

and cleanliness cannot be achieved simultaneously). At the same time, the operational mechanisms, innovation capabilities, and business performance are different for enterprises at different lifecycle stages [14], and therefore conducting a comparative analysis of the impacts of technological innovation efficiency on enterprises at different stages can help to formulate the technology-driven paths and development strategies tailored to their own conditions. From this perspective, the major contributions of this research are as follows: (1) This article takes 81 new energy enterprises in China as the research objects and measures their technological innovation efficiency from 2016 to 2021 by using a stochastic frontier model based on the transcendental logarithmic function from the perspective of lifecycle stages. Thus, the research perspective of an enterprise's technological innovation efficiency analysis can be expanded, and the impact of random error terms is considered, which can improve the accuracy of efficiency calculation. (2) Non-financial indicators, such as environmental, social, and governance (ESG) performance and enterprise size, are incorporated into the enterprise growth-evaluation index system and case evaluations are conducted by combining the entropy weight method and the catastrophe progression method. Thus, it can make up for the deficiency that the existing research ignores the important impact of non-financial indicators on the growth level of enterprises. (3) On this basis, the heterogeneity effect of technological innovation efficiency on their growth at different lifecycle stages is investigated deeply and comprehensively by using a fixed-effect model, and, finally, targeted development suggestions are proposed to enable them to achieve healthy and sustainable development through innovation.

Investigating the driving mechanisms of technological innovation is helpful to promote the upgrading and development of new energy enterprises. It helps meet fierce competitive demand and increase market share, which is especially critical to the long-term success of energy enterprises. Therefore, this study is helpful to fully understand the technological innovation efficiency level and overall growth level of new Chinese energy enterprises. Meanwhile, by introducing the lifecycle stage perspective, it can contribute heterogeneous technological innovation development strategies to new energy enterprises at different growth stages. This not only provides goal orientation and path guidance for achieving high-quality innovation, but also helps listed enterprises to gain a foothold in the global market through technological empowerment, and is of great significance for the sustainable development of the whole society.

The rest of this article is structured as follows: Section 2 presents a relevant literature review. Section 3 presents a theoretical analysis and the research hypotheses. Section 4 focuses on the research design. Section 5 presents the empirical analysis results. Section 6 presents the main conclusions and policy implications.

2. Literature Review

2.1. Technological Innovation Efficiency

Technological innovation efficiency involves both innovation input and output, and therefore can reflect the level of technological innovation in an enterprise comprehensively. Tone pointed out that effective efficiency means producing more expected outputs and less unexpected outputs with less input [15]. The higher the technological innovation efficiency, the higher the business revenue and the more the technological innovation can support the development of the enterprises, with the same input of production factors such as R&D personnel and funds.

Parametric and non-parametric methods are the two main ways to measure technological innovation efficiency in current research. The parametric method is represented by stochastic frontier analysis (SFA), which decomposes the deviation between the actual production unit and the frontline into random errors and technical inefficiency, and estimates the frontline production function by using econometric methods [16]. The SFA method was first proposed by Aigner et al. [17], and subsequently other scholars continuously expanded

the research scope of this method to enhance its applicability. Haider et al. [18] used the SFA model to explore the effect of innovation on the energy efficiencies of steel enterprises. Piao et al. [19] used this model to calculate the technological innovation efficiency of energy enterprises and the research results showed that their technological innovation efficiencies were lower than the effective state and showed a declining trend, and that new energy enterprises have higher efficiencies than traditional energy enterprises. Hussein et al. [20] used panel data and a stochastic frontier method based on the Cobb Douglas production function to evaluate technological efficiency and economic openness at the macro level. Niu et al. [21] adopted the SFA model to calculate the green utilization efficiency of urban land by taking composite indicators as output indicators. The non-parametric method is represented by data envelopment analysis (DEA), which can calculate the relative efficiency of the research objects based on a linear programming model and can ideally reflect their characteristics. In 1978, operations researcher Charnes et al. [22] assumed that the returns from the production scale remained constant and proposed a data envelopment analysis model called CCR for the first time to evaluate the technological efficiency of decision-making units. Subsequently, other scholars further proposed different models to meet the actual needs of their research, such as BCC [23], Malmquist [24], SBM [25], EBM [26], and three-stage DEA [27]. DEA is still the main research model adopted in academia. Chen et al. [28] measured the technological innovation efficiency of renewable energy enterprises in the Chinese A-share stock market based on the three-stage DEA model. The study showed that although the technological innovation efficiency of renewable energy enterprises has steadily improved, there is still some room for improvement. Guan et al. [29] constructed a two-stage DEA model for a typical innovative production process (IPP) and measured the technological innovation efficiency at the development and application stages, respectively. Zhong et al. [30] adopted a three-stage DEA model to study the technological innovation efficiency of high-tech industries at the provincial level and analyzed the efficiency-influencing factors from internal management and the external environment.

2.2. Enterprise Growth

The existing research on enterprise growth mainly focuses on the evaluation of their growth levels, but enterprise growth is a complex and comprehensive indicator influenced by multiple factors and its evaluation relies on scientific and effective methods. Currently, the main evaluation methods in the academic research include regression analysis [31], factor analysis [32], the catastrophe progression method, the entropy weight method [33], etc. Regression analysis utilizes the principles of data statistics to process a large amount of statistical data mathematically, establishes a regression equation with good correlation, and determines the correlation and degree of interaction between the dependent variables and certain independent variables [34]. Factor analysis is a multivariate statistical analysis method to estimate the impact of latent factors on measurable variables and the correlation between latent factors [35]. The above two methods are more often used to determine the impact of relevant factors on corporate growth. The catastrophe progression method is a fuzzy function theory deduced from catastrophe theory and calculus theory. It is a comprehensive evaluation method to calculate the quantitative values of each target through a catastrophe subordinate function and normalization formula and to perform comprehensive normalization quantification computation. As an evaluation method to obtain objective indicator weights, the entropy weight can calculate the entropy weight of each indicator with information entropy and modify the weight of each indicator with entropy weight according to the dispersion of the indicator data [36]. Compared with the entropy weight method, the catastrophe progression method can calculate indicator values through normalization formulas, which helps to display the relative importance of each indicator but lacks an objective weighting process for these indicators [37].

In the existing research, financial indicators are adopted to evaluate enterprise growth. Tang et al. [38] established an evaluation indicator system for enterprise growth from four dimensions: operational ability, debt-paying ability, profitability, and development ability. The result pointed out that financial indicators can reflect enterprise growth comprehensively because they are based on the overall development situation of enterprises. Ma et al. [39] identified the influencing factors of enterprise growth from four perspectives: debt-paying ability, development ability, operational ability, and profitability. Among these, profitability and debt-paying ability were found to be the two key indicators that can best reflect enterprise growth through their empirical analysis.

With the advancement of theory, non-financial indicators have been gradually incorporated into the evaluation of enterprise growth. Fang et al. found in their research that the comprehensiveness and scientificity of the evaluation indicator system can be enhanced by incorporating non-financial indicators [40]. At the same time, the importance of ESG performance, as a non-financial indicator, in the evaluation of enterprise growth has gradually attracted attention. Pacelli et al. [41] suggested that good ESG performance by a company can enhance its image, win the trust and support of investors, and enhance its ability to withstand risks and crises. The 2022 Global Economic Risk Report released by the World Economic Forum shows that in the next 10 years, five ESG-related risks are among the top ten economic risks in terms of their probability of occurrence and severity. Orzes et al. [42] conducted empirical research on 810 multinational and cross-industry companies and found that corporate social responsibility has a positive impact on the sales quota of enterprises. Thanh et al. [43] constructed a framework for analyzing the influence of corporate social responsibility on performance, and the results showed that the efforts of enterprises to promote the advancement of society and protect the environment and the efforts of the employees and other stakeholders to fulfill their social responsibilities are very important in retaining customers and sustaining businesses and have a positive influence on their growth. Abdi et al. [44] found that participation in social and environmental activities will bring high levels of financial efficiency in return, and ESG performance has a positive influence on corporate value.

2.3. The Relationship between Technological Innovation and Enterprise Growth

The relationship between technological innovation and enterprise growth includes positive correlations, negative correlations, and other related relationships. Wang [45] used data from listed enterprises on the Science and Technology Innovation Board from 2019 to 2021 to analyze the influence of technological innovation on corporate growth at different stages. The results showed that investment in R&D has a positive impact on corporate growth. Wei et al. [46] found that development-oriented technological innovation has a negative influence on corporate growth by taking 176 Chinese enterprises as a sample database, and this negative impact will be worsened by an efficiency-centered business model. Kim et al. [47] studied the relationship between technological innovation and corporate growth by taking Korean manufacturing enterprises as research samples. The study showed a U-shaped relationship between technological innovation and enterprise growth, indicating that both insufficient and excessive technological innovation will be detrimental to corporate growth. At the same time, the relationship can be adjusted by mitigating the harmful effects of excessive technological innovation on the core technology.

In recent years, scholars have begun to analyze the relationship between technological innovation and corporate growth from the perspective of efficiency. Homma et al. studied the relationship between corporate efficiency and growth level [48]. Rubén et al. [49] analyzed the influence of technological innovation efficiency on enterprise growth based on paired design and ordinary least squares regression by taking 152 Spanish manufacturing enterprises as research samples. The study showed a positive effect of technological innovation efficiency on corporate growth, and the relationship can be strengthened by long-term

cooperation between manufacturing enterprises and their stakeholders based on tacit knowledge and social capital. The energy industry pays more attention to the research on the influence of technological innovation on enterprise performance. Li et al. [50] analyzed the impact of green innovation on sustainable growth (including financial, environmental, and social performance) in energy-intensive industries from the perspective of managers. Liang et al. [51] studied the data from 136 Chinese energy companies from 2009 to 2019 and found through empirical research that technological innovation can improve the environmental performance of energy companies and provide good development opportunities for traditional energy companies.

It can be found from the above literature review that although some research has been conducted on technological innovation, enterprise growth, and their relationship, the following aspects still need improvement. Firstly, existing studies mainly adopt the DEA method to measure technological innovation efficiency because it does not require pre-set production functions and the analysis process is convenient. However, the traditional DEA model cannot distinguish the impact of the external environment and random errors, is sensitive to outliers, and is easily affected by extreme values, making it difficult to achieve an objective evaluation [52]. Therefore, in order to reduce the impact of random errors on measurement results, control the fluctuation of outliers caused by “black swan events” such as COVID-19, and improve the calculation accuracy of panel data, it is necessary to conduct research on technological innovation efficiency based on parametric methods such as SFA [53]. Secondly, in the existing research on enterprise growth, financial indicators such as profitability are widely adopted due to data availability and objectivity. However, the significant impact of non-financial indicators such as ESG performance and enterprise size on enterprise growth is ignored to some extent, and therefore the lack of comprehensiveness in such research makes its research results unable to meet practical needs. Thirdly, more research focuses on cross-sectional differences, while comparative analysis based on time dimensions is relatively less prevalent. However, the truth is that enterprises at different lifecycle stages have different operating mechanisms, innovation capabilities, and business performance and, therefore, ignoring these differences is not conducive to finding targeted and practical technology-driven paths [54]. Thus, it is necessary to explore and analyze the heterogeneity effects from a lifecycle perspective.

3. Theoretical Analysis and Research Hypotheses

3.1. Direct Effect

Technological innovation, capital investment, and new markets are the three driving forces in developing new energy enterprises [55]. Being highly technology-intensive is a characteristic of new energy enterprises and technology innovation can bring sustained vitality and long-term core competitiveness to enterprises by reducing factor input and optimizing resource allocation [56]. Specifically, on the one hand, the enhancement of technological innovation efficiency will simultaneously improve the conversion efficiency of scientific research achievements, reduce the cost of R&D, and increase the economic benefits; on the other hand, a higher technological innovation efficiency will bring new technologies, processes, and products. Optimizing resource allocation in the production process can help improve production efficiency, avoid resource waste, and reduce production costs. The theory of enterprise growth believes that the reasonable utilization of internal resources is the key to achieving core competitiveness and sustainable development. Technological innovation efficiency can reflect resource allocation in enterprises effectively and its improvement is conducive to maximizing the utilization of enterprise funds, improving its production and management, and bringing enough space and opportunities for development. Therefore, hypothesis H1 is proposed:

H1. *From the perspective of lifecycle stages, the improvement of technological innovation efficiency has a positive impact on the growth of new energy enterprises.*

3.2. Intermediary Effect

Technological innovation can stimulate the growth of new energy enterprises through price increases, cost reduction, and market expansion. Among them, expanding the market share is the most direct and significant way to enhance enterprise growth [57,58]. A high technological innovation efficiency can enable them to respond quickly to the market, obtain cost effects and economic effects through innovation, and protect and expand their market share by establishing competitive advantages [59]. Market share, to some extent, reflects the position of a new energy enterprise in the whole industry. The larger the market share, the higher the recognition of this enterprise in the market, and the stronger this enterprise can control the market. With the continuous expansion of the market share and the formation of scale effects, a new energy enterprise can take a dominant position in the market, which can bring large profits, obtain competitive advantages, and comprehensively enhance its growth. Therefore, hypothesis H2 is proposed:

H2. *A higher technological innovation efficiency can protect and expand market share, thereby comprehensively enhancing the growth of new energy enterprises.*

3.3. Heterogeneity Effect

The theory of the enterprise lifecycle was first proposed by American management scientist Ichak Adizes in his research on the survival and development of enterprises. This theory believes that the life of enterprises, like the other things in the world, follows a lifecycle from birth to decline and enterprises at different lifecycle stages exhibit differentiated characteristics, thus defining the law of lifecycles in enterprise development [60]. Due to the different characteristics of enterprises in resource accumulation, system structure, and management capabilities at different stages, the impact of technological innovation efficiency on their growth will also show some differences.

Given that most of the new, listed energy enterprises have already gone through the start-up period characterized by insufficient financial resources and currently have a certain scale and capital accumulation, this article divides them into growing, mature, and declining stages based on the division method proposed by scholar Dickinson [61].

3.3.1. Growing Enterprise

After the early preparation and establishment of channels, enterprises in the growing stage are now on the right track of operation. By now, they already have a certain fund accumulation and are in a critical period of rapid development. However, the rapid development speed will also, to some extent, lead to insufficient production capacity or product quality being unable to meet the constantly increasing customer needs [62]. At this time, only imitating the advanced technology from other enterprises cannot support their development. To achieve better development and further expand their market share, enterprises are supposed to enhance their own technological innovation capabilities so as to obtain the advantage of technological barriers. At this stage, on the one hand, a higher technological innovation efficiency can improve product quality, enrich product variety, reduce production costs continuously, and further expand market share. On the other hand, more financial support can be given to production and operation, market promotion, and other activities by better utilizing R&D funds [63]. Therefore, the improvement of technological innovation efficiency helps to provide strong support for growing enterprises to expand their production and business scale. Therefore, hypothesis H3a is proposed:

H3a. *The improvement of technological innovation efficiency has a positive impact on the growth of growing enterprises.*

3.3.2. Mature Enterprise

Mature enterprises boast high brand recognition and the strongest profitability in the entire lifecycle, and their market share, production efficiency, and organizational structure are all in a stable condition. They have a strong will and sufficient funds to carry out research and innovation in order to have a bigger competitive advantage [64]. Thanks to the accumulation of experience and funds in the early development stage, their organization and management capabilities in innovation have been significantly improved, relatively mature technical teams and clear research directions have been established, and the output efficiency of R&D has reached a high level. They also boast sufficient supporting resources for innovation [65]. With the continuous enhancement of technological innovation efficiency, they can quickly take the lead in the industry, achieve a certain monopoly effect, enhance their profitability and expansion, and improve their own growth. Therefore, hypothesis H3b is proposed:

H3b. *The improvement of technological innovation efficiency has a positive impact on the growth of mature enterprises.*

Compared with growing enterprises, the R&D of mature enterprises focuses on ground-breaking technological innovation in the industry, and their business focus is gradually shifting towards market development and institutional innovation [66]. Their survival and development no longer rely mainly on technological innovation, so the impact of technological innovation efficiency on their growth is less than that of growing enterprises. Therefore, hypothesis H3c is proposed:

H3c. *The growth of mature enterprises is less affected by technological innovation efficiency than that of growing enterprises.*

3.3.3. Declining Enterprise

Declining enterprises face a lot of difficulties and challenges, such as low profitability, a shrinking market share, a lack of financial support in R&D, outdated technology and equipment, and low conversion rates of technological research. For them, one of the important development strategies to achieve “rebirth” is to innovate their technology, because improving their technological innovation efficiency can reduce the risk of R&D failure, grasp new opportunities in the market, and ultimately enhance their growth. However, improving technological innovation efficiency relies on advanced equipment and sufficient funds, and consequently they may have to bear greater investment risks because the economic benefits brought by technological innovation may not compensate for the increased cost [67]. At the same time, problems such as overstaffing in their internal organizations and a constantly decreasing operational efficiency are gradually becoming more serious, and therefore technology is no longer a key factor affecting their development. In summary, improving technological innovation efficiency may have little driving effect on their development and may actually have a negative impact on their growth. Therefore, hypothesis H3d is proposed:

H3d. *The impact of improving technological innovation efficiency on the growth of declining enterprises is uncertain, and may even have a negative impact.*

A theoretical model displaying the relationship between technological innovation efficiency and enterprise growth is constructed based on resource signal theory and lifecycle theory, as shown in Figure 1.

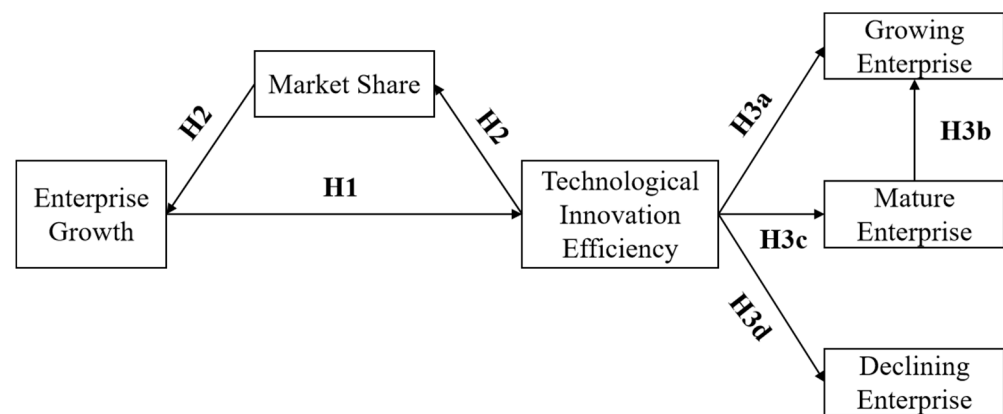


Figure 1. Research framework.

4. Research Design

4.1. Measurement of Technological Innovation Efficiency

The basic concept of the stochastic frontier method is to determine the production frontier of technological innovation via production function and random disturbance terms, estimate parameter values through the maximum likelihood method, and then treat the conditional expectation of the technological inefficiency terms as the technological efficiency value [68]. This method takes the impact of random error terms into full consideration and can improve the accuracy of calculating technological innovation efficiency. The analysis results are relatively stable and not affected by outliers. The specific model is as follows.

Suppose the output of decision-making unit i is

$$y_{it} = f(x_{it}, \beta) \zeta_{it} \quad (1)$$

In this equation, $f(x_{it}, \beta)$ is the production function; x_{it} is the input variable set of decision-making units i ; ζ_{it} is the efficiency value of decision-making unit i with a value range of $(0, 1]$. When $\zeta_{it} = 1$, it indicates that the decision-making unit is at the production frontier.

However, the production of decision-making units is likely to be influenced by random factors, and therefore the output of decision-making unit i is set as

$$y_{it} = f(x_{it}, \beta) \zeta_{it} e^{v_{it}} \quad (2)$$

In this equation, $e^{v_{it}}$ is a random disturbance term, representing the impact of random factors on the production of the decision-making unit.

Equation (3) can be obtained by taking the logarithms of the left and right sides of Equation (2):

$$\ln y_{it} = \ln[f(x_{it}, \beta)] + \ln \zeta_{it} + v_{it} \quad (3)$$

Since the value range of ζ_{it} is $(0, 1]$, then $\ln \zeta_{it} \leq 0$, and we assume that $u_{it} = -\ln \zeta_{it}$. Then, Equation (3) can be transformed into

$$\ln y_{it} = \ln[f(x_{it}, \beta)] + v_{it} - u_{it} \quad (4)$$

In this equation, $\ln[f(x_{it}, \beta)] + v_{it}$ is the production frontier and also represents the ideal production state, and u_{it} represents the technical inefficiency term.

The general form of a stochastic frontier production function model can be expressed as follows:

$$y_{it} = f(x_{it}, \beta) e^{v_{it} - u_{it}} \quad (5)$$

One can set the difference between the actual output and the ideal output of the decision-making unit as u_{it} , and then the efficiency TE_{it} can be expressed as

$$TE_{it} = \frac{E[f(x_{it}, \beta)e^{v_{it}-u_{it}}]}{E[f(x_{it}, \beta)e^{v_{it}}]} \quad (6)$$

The production functions set by the stochastic frontier method are also constantly improving. Currently, the Cobb Douglas (C-D) production function and the transcendental logarithmic (Translog) production function are most commonly used. Referring to Chatzimeichael's research [69], compared to the C-D production function, the Translog production function shows better applicability and inclusiveness since it is not constrained by Hicks-neutral technological progress and input-output elasticity fixed assumptions. Therefore, a stochastic frontier model based on the Translog production function was selected to calculate the technological innovation efficiency of new Chinese energy enterprises in this paper. Based on the stochastic frontier model framework [70], a production frontier model was constructed here to maximize innovation output by investing the same production factors, such as manpower and funds. The specific equation of the model is as follows:

$$\ln y_{it} = \beta_0 + \beta_1 \times \ln L_{it} + \beta_2 \times \ln K_{it} + \beta_3 \times t + \beta_4 \times (\ln L_{it})^2 + \beta_5 \times (\ln K_{it})^2 + \beta_6 \times t^2 + \beta_7 \times \ln K_{it} \times \ln L_{it} + \beta_8 \times t \times \ln K_{it} + \beta_9 \times t \times \ln L_{it} + v_{it} - u_{it} \quad (7)$$

In the equation, y is the current operating revenue of the enterprise, representing its technological innovation output; L is the full-time equivalent of R&D personnel, representing the manpower in its R&D; K is the R&D capital stock [71], representing its R&D funds; u_{it} is the technical inefficiency term, and it follows non-negative truncated normal distribution; $u_{it} \sim N(m_{it}, \sigma_u^2)$, v_{it} , and u_{it} are independent and uncorrelated [72]; m_{it} is the stage point of non-negative truncated normal distribution, and $m_{it} = z_{it}\delta$ (z_{it} is an exogenous variable vector that affects the technological innovation efficiency, and δ is the parameter vector of exogenous variables to be estimated) [73]; i and t are the serial numbers of the enterprises and years, respectively; $\beta_0 \sim \beta_9$ and η all are parameters to be estimated, in which η represents the impact of time on the technical inefficiency term. $\eta > 0$ indicates that the impact decreases over time, $\eta = 0$ means the impact remains unchanged over time, and $\eta < 0$ means the impact increases over time [74].

Because the technical inefficiency term is introduced into the stochastic frontier method [75], it is necessary to set its functional equation. By analyzing the factors affecting the technological innovation output of new Chinese energy enterprises, and referring to the research of Lin et al. [76], Qiao et al. [77], Xia et al. [78], and Ma et al. [79], the profitability, government support, and the proportion of state-owned capital are selected as environmental variables. The inefficiency term is set as follows:

$$u_{it} = \delta_0 + \delta_1 \text{PRO} + \delta_2 \text{GOV} + \delta_3 \text{OWN} \quad (8)$$

In the equation, PRO is the profitability of the enterprise, represented by its current net profit; GOV is government support, represented by the proportion of government subsidies to the total investment in technological innovation in that year; OWN is enterprise ownership, represented by the proportion of state-owned equity to the total equity in the enterprise; and $\delta_0 \sim \delta_3$ is the parameter to be estimated, representing the impact on the technological innovation efficiency.

4.2. Enterprise Growth Evaluation

4.2.1. Construction of Index System

As complex economic entities, new, listed energy enterprises are influenced by multiple factors in their growth and development. The traditional growth evaluation system mainly involves financial factors [38,39], and considers the impact of environmental, social, and corporate governance performance, enterprise size, and other factors less, so it can-

not comprehensively evaluate enterprise growth [40]. In order to accurately measure the growth level of new Chinese energy enterprises and balance financial and non-financial indicators, a comprehensive indicator evaluation system was constructed as shown in Table 1.

Table 1. Comprehensive indicator evaluation system for growth level.

First-Level Indicators	Second-Level Indicators	Third-Level Indicators	Calculation Formula
Growth level of new energy enterprises	Financial indicators	Profitability	Return on equity Ratio of profits to cost Return on assets
			Net profit/Net assets Total profit/Total cost (Net profit + Interest expense)/Average total assets
		Operation capacity	Current asset turnover Inventory turnover Account receivable turnover Total assets turnover
			Prime operating revenue/Average current assets Prime operating cost/Average inventory occupancy Operating revenue/Average accounts receivable Prime operating revenue/Average total assets
	Development ability	Total assets growth rate	(Closing total assets-beginning total assets)/Beginning total assets
		Capital accumulation rate	(Closing owner equity growth amount-beginning owner equity growth amount)/Beginning owner equity growth amount
		Operating profit growth rate	(Closing operating profit-beginning operating profit)/Beginning operating profit
	Non-financial indicators	Environmental, social, and governance (ESG) performance	ESG scores released by Sino-Securities Index Information Service (Shanghai, China) Co. Ltd.
		Size	Total assets Number of workers Total enterprise assets Total number of enterprise workers

4.2.2. Evaluation Model

The catastrophe progression method involves indicator ranking in the evaluation process. Subjective methods such as expert evaluation are often used to determine the ranking, which increases the subjective influence of human factors and reduces the reliability of the evaluation results [80]. The entropy weight method is a method of objective weighting, and its basic idea is to determine the weight according to the amount of information contained in the index entropy value [36]. In order to effectively avoid the influence of subjective factors, the weight calculated by the entropy weight method can be used as the basis of indicator ranking. In order to ensure more objective and scientific evaluation results, the growth of new Chinese energy enterprises is evaluated by combining the entropy weight method and the catastrophe progression method. Firstly, the entropy weight method is used to determine the relative importance of first- and second-level evaluation indicators, and then the catastrophe progression method is used to normalize the third-level indicators. Finally, a comprehensive evaluation of enterprise growth is conducted through weighted summation. The specific evaluation steps are as follows:

(1) Data standardization

Firstly, the range transformation method is used to standardize x_{ij} , the j th evaluation indicator of the i th decision-making unit. The selected indicators are all positive indicators, so the standardization equation is

$$y_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \quad (9)$$

(2) Determine index weights using the entropy weight method

- Calculate p_{ij} , the proportion of x_{ij} :

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (10)$$

- Calculate e_j , the entropy weight of the j th indicator:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln p_{ij} (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (11)$$

- Calculate h_j , the difference coefficient of the j th indicator:

$$h_j = 1 - e_j \quad (12)$$

- Calculate w_j , the weight of the j th indicator:

$$w_j = \frac{h_j}{\sum_{j=1}^n h_j} \quad (13)$$

(3) Determine the growth score with the catastrophe progression method

- According to catastrophe progression theory, there are mainly four common catastrophe system types:

A. The folding catastrophe system model (with one control variable):

$$f(x) = x^3 + ax \quad (14)$$

The normalization equation is $x_a = a^{\frac{1}{2}}$.

B. The cusp catastrophe system model (with two control variables):

$$f(x) = x^4 + ax^2 + bx \quad (15)$$

The normalization equation is $x_a = a^{\frac{1}{2}}, x_b = b^{\frac{1}{3}}$.

C. The swallowtail catastrophe system model (with three control variables):

$$f(x) = \frac{1}{5}x^5 + \frac{1}{3}ax^3 + \frac{1}{2}bx^2 + cx \quad (16)$$

The normalization equation is $x_a = a^{\frac{1}{2}}, x_b = b^{\frac{1}{3}}, x_c = c^{\frac{1}{4}}$.

D. The butterfly catastrophe system model (with four control variables):

$$f(x) = \frac{1}{6}x^6 + \frac{1}{4}ax^4 + \frac{1}{3}bx^3 + \frac{1}{3}cx^2 + dx \dots \quad (17)$$

The normalization equation is $x_a = a^{\frac{1}{2}}, x_b = b^{\frac{1}{3}}, x_c = c^{\frac{1}{4}}, x_d = d^{\frac{1}{5}}$.

In the equation, x is the state variable; $f(x)$ is the potential function of x ; the coefficients a, b, c , and d are the control variables of x , and they are ranked by importance; and x_a, x_b, x_c , and x_d are the corresponding catastrophe values of the control variables.

- Normalization calculation and comprehensive evaluation.

Considering the complementary relationship between the evaluation indicators of enterprise growth, the calculation is carried out by taking the average values of these indicators. The detailed calculation is as follows: first, the third-level indicators are normalized one by one with the catastrophe progression method, and the mean values of the normalized third-level indicators are taken as the base values of second-level indicators. And then, the enterprise growth score is ultimately calculated by making weighted summation of the first- and second-level indicators one by one.

4.3. Multiple Regression Analysis of Impact Effects

4.3.1. Selection of Research Variables

- (1) Explained variable. Enterprise growth (EG) reflects the development potential of new energy enterprises. The calculated enterprise growth score based on the comprehensive indicator evaluation method in Section 3.2 is adopted here to represent enterprise growth.
- (2) Explanatory variable. Technological innovation efficiency (TE) reflects the technological innovation ability of new energy enterprises. Based on the output of technological innovation and the input of R&D manpower and funds, the above stochastic frontier method is used for efficiency evolution, which will not be repeated here.
- (3) Mediating variable. Market share (MS) reflects the market shares of new energy enterprises. It is calculated by the relative market share method, and the calculating equation is “research enterprise sales/sales of leading enterprises in the market”.
- (4) Control variables:
 - Government support (GOV). As an effective means to rectify externalities and compensate for market failures, it mainly supports new energy enterprises through financial allocation, tax returns, interest subsidy, government guarantees, legal protection, and other channels. It will lower the entry barriers into the new energy industry, guide innovation directions, fully convey a positive image of the development prospects of enterprises to investors, expand funding sources, and enhance the profitability of enterprises [81]. The natural logarithm of government subsidy funds is used to represent government support.
 - Asset size (SIZE). This reflects the operating ability of an enterprise to a certain extent and usually has a positive impact on its growth. Large-scale enterprises have obvious advantages in the economy of scale, risk diversification, financing channels, and innovation capabilities, which is conducive to reducing their overall operating costs and enhancing their competitiveness in the market to obtain a monopoly position [82]. This paper selects the natural logarithm of the year-end total assets of a company to represent the asset size.
 - Age of establishment (AGE). Generally speaking, growing enterprises are in a period of rapid expansion with fast growth and a strong will to innovate. Their innovation ability will reach the highest point after entering a period of high-speed development with their continuous accumulation of funds, technology, and talent. Afterwards, they may face bottlenecks in their development in technology, capital, and the market. Influenced by complex internal and external factors, their development speeds gradually slow down [83].
 - Equity concentration (EC). The equity structure can reflect the governance structure of a company. When the EC of a company is high, controlling shareholders have more say in decision making. The reasonable allocation and supervision of business activities by controlling shareholders will have a positive impact on a business's growth [84]. However, when they have a conflict of interest with other small- and medium-sized shareholders, they may act recklessly and make wrong decisions, which will affect normal business operations and ultimately have a negative impact on their growth. This paper adopts the ratio of the top five shareholders' equity to the total equity of the enterprise to represent EC.

- Financial leverage (LEV). This reflects the ability of an enterprise to utilize its financial liabilities. Reasonable use of financial leverage can provide sufficient financial support for a business, more growth opportunities, and more development space, but unreasonable use may lead to serious financial risks and hinder its growth [85]. This paper selects the year-end asset–liability ratio of a company to represent its financial leverage.

Table 2 shows descriptive statistics for the main variables (mean, standard deviation, and minimum and maximum values).

Table 2. Descriptive statistics of variables.

Variables	Minimum	Maximum	Mean	Standard Deviation	Sample Size
EG	0.542	0.972	0.788	0.079	486
TE	0.868	1.000	0.908	0.017	486
MS	0.008	1.000	0.646	0.194	486
GOV	9.504	21.779	17.515	1.548	486
SIZE	19.55	26.74	23.45	1.264	486
AGE	8.000	37.000	20.720	5.782	486
EC	17.800	95.290	55.213	15.911	486
LEV	0.057	0.894	0.707	0.117	486

4.3.2. Benchmark Model

- (1) Analysis model of the impact of technological innovation efficiency on enterprise growth

To study the relationship between technological innovation efficiency and the growth of new Chinese energy enterprises, EG is taken as the explained variable, TE is taken as the explanatory variable, and, at the same time, GOV, LEV, SIZE, AGE, and EC are treated as control variables. Model M1 is set as follows:

$$M1 : EG_{it} = \beta_0 + \beta_1 TE_{it} + \beta_2 GOV_{it} + \beta_3 LEV_{it} + \beta_4 SIZE_{it} + \beta_5 AGE_{it} + \beta_6 EC_{it} + \lambda_i + \delta_t + u_{it} \quad (18)$$

In the equation, i represents the serial number of the sample enterprises; t is the year; β_0 is a constant term; $\beta_1 \sim \beta_6$ are parameters to be estimated; λ_i is the individual fixed effect; δ_t is the time fixed effect; and u_{it} is a stochastic disturbance term.

- (2) An analysis model taking mediating effects into consideration

To clarify the mediating role of MS in the impact of TE on EG, models M2 and M3 are set as follows:

$$M2 : MS_{it} = \beta_0 + \alpha TE_{it} + \beta_2 GOV_{it} + \beta_3 LEV_{it} + \beta_4 SIZE_{it} + \beta_5 AGE_{it} + \beta_6 EC_{it} + \theta_i + \gamma_t + \mu_{it} \quad (19)$$

$$M3 : EG_{it} = \beta_0 + k MS_{it} + \beta_1 TE_{it} + \beta_2 GOV_{it} + \beta_3 LEV_{it} + \beta_4 SIZE_{it} + \beta_5 AGE_{it} + \beta_6 EC_{it} + \sigma_i + \eta_t + \rho_{it} \quad (20)$$

In the equation, α , k , and $\beta_1 \sim \beta_6$ are the parameters to be estimated; θ_i and σ_i are the individual effects; γ_t and η_t are the time fixed effects; and μ_{it} and ρ_{it} are stochastic disturbance terms.

4.4. Research Sample and Data Source

Considering the consistency and availability of data, we selected new, listed energy companies in China's A-share market from 2016 to 2021 as the research samples. According to the Classification of Strategic Emerging Industries (2018) released by the National Bureau of Statistics, new energy businesses mainly include nuclear energy, wind energy, solar energy, biomass energy, and other new energy sources. To satisfy the needs of the research, enterprises with new energy revenue accounting for less than 50%, enterprises listed later than 2016, special treatment (ST) enterprises with abnormal financial or other conditions, and enterprises with significant data gaps were eliminated from the research. Finally, 81 eligible enterprises were selected, and they can objectively reflect the overall situation of new Chinese energy enterprises.

In order to conduct heterogeneity research from a lifecycle perspective, the lifecycle stages of new energy enterprises should be determined first. The commonly used classification methods in the academic community currently include univariate analysis [86], comprehensive indicator analysis [87], and the cash flow combination method [88]. Among them, the first two methods both have a certain degree of subjectivity, while the third method can divide an enterprise's lifecycle stages more accurately by considering the characteristics of these three indicators: operational cash flow, investment cash flow, and financing cash flow. It can reflect the characteristics of resource allocation, operational capacity, and strategy selection of an enterprise, and boasts high sensitivity and accuracy. Additionally, there is no need to verify the linear relationship between the various factors and lifecycle stages. Therefore, it was ultimately adopted in this paper to divide the lifecycle stages. The basis for dividing the lifecycle stages of new energy enterprises based on the cash flow combination method is shown in Table 3 [62,89,90], where “+” and “−”, respectively, represent an increase or decrease in cash flow.

Table 3. Standard for dividing enterprise lifecycle.

	Growing Stage		Mature Stage	Declining Stage		
	Early Period	Later Period		Declining Period 1	Declining Period 2	Declining Period 3
Operating cash flow	−	+	+	−	−	−
Investing cash flow		−	−	−	+	+
Financing cash flow		+	−	−	+	−

Based on the cash flow combination method, the lifecycle stages of the 81 sample enterprises were determined according to the standard for dividing enterprise lifecycles in Table 3 and their operating, investing, and financing cash flows from 2016 to 2021. In total, 39 of them were in the growing stage, 27 in the mature stage, and 15 in the declining stage. The specific division results are shown in Table 4.

Table 4. Results of enterprise lifecycle stage division.

Lifecycle Stages	Enterprise Abbreviation
Growing stage	Shenzhen Energy, Dongxu Lantian, Shaoneng Co., Ltd., Guoxuan High tech, Zhongcai Technology, Kelu Electronics, TCL Zhonghuan, Jinfeng Technology, Tuori New Energy, Aotexun, North Huachuang, Duofuduo, Jiangsu Shentong, Ganfeng Lithium Industry, Tianshun Wind Energy, Changqing Group, Shouhang High tech, Yiwei Lithium Energy, Xingzhoubang, Dongfang Risheng, Tongyu Heavy Industry, Sunshine Power, Zhonglai Co., Ltd., Shanghai Electric Power, TBEA, Tongwei Co., Ltd. Hengtong Optoelectronics, State Grid Yingda, Zhongtian Technology, Yijing Optoelectronics, Shanshan Co., Ltd., Longji Green Energy, Jieneng Wind Power, Bowei Alloy, Linyang Energy, Shanghai Electric, Zhengtai Electric, Jing Yuntong, China Nuclear Power
Mature stage	Nanbo A, Solar Energy, Silver Star Energy, COFCO Technology, Tianqi Group, Hengdian Dongci, Suzhou Guzhen, Wole Nuclear Materials, Dalian Heavy Industry, Dajin Heavy Industry, Xiexin Integration, Keshida, Aikang Technology, Amaden, Yilida, Zhongneng Electric, Yicheng New Energy, Jingsheng Electromechanical, Dyson Group, Aerospace Electromechanical, Guiguan Electric, Xiangdian Group, Times New Materials, Wolong Electric Drive, Zongyi Co., Ltd, Changjiang Electric, Dongcai Technology
Declining stage	Fosu Technology, Jinggong Technology, Xiexing Energy Technology, Dongfang Zirconia Industry, Zhaoxin Co., Ltd., Jingang Photovoltaic, Lingda Co., Ltd., Taisheng Wind Energy, Jiawei New Energy, Yishite, Harbin Air Conditioning, Shuangliang Energy Conservation, Chuantou Energy, Dongfang Electric, Foster

The basic data of this study come from the CSMAR database, the RESSET database, the WIND database, the China Innovation Patent Research Database (CIRD), the official website of the China National Intellectual Property Administration (SIPO) (<http://epub.cnipa.gov.cn/>, accessed on 1 October 2023), the Shenzhen Stock Exchange, the Shanghai Stock Exchange, etc., and some data come from the annual reports of sample enterprises and were compiled and sorted by the authors.

5. Empirical Analysis

Schumpeter's theory of innovation points out that technological innovation is the fundamental productive force of social development [91]. It is impossible to upgrade products and services only by rigid production mechanisms, and the forward development of enterprises depends on efficient technological innovation. Through continuous technological innovation, the existing resources of enterprises can be used flexibly to the maximum extent, and the process and quality can be improved, so as to improve production efficiency and manufacture better products, thus achieving the highest economic benefits. The realized economic benefits can also bring a steady stream of power to technological innovation. Finally, a virtuous circle will be realized, so that enterprises have the motivation to grow continuously. The following is an empirical analysis of the impact of technological innovation efficiency on the growth of new energy enterprises.

5.1. Technological Innovation Efficiency of New Chinese Energy Enterprises

Parameter estimation of the previously constructed stochastic frontier model was carried out, and the results are shown in Table 5.

Table 5. Parameter estimation results of stochastic frontier model.

Production Function			Technical Inefficiency Function		
Variables	Coefficient Estimates	t-Value	Variable	Coefficient Estimates	t-Value
Constant term	18.98	19.74 ***	Constant term	−1.15	−1.08
$\ln L_{it}$	−22.92	−25.62 ***	PRO	−0.06	−1.85 *
$\ln K_{it}$	−2071.78	−2315.28 ***	GOV	−1.06	−9.19 ***
t	−1.46	−4.78 ***	OWN	0.43	2.27 **
$(\ln L_{it})^2$	−11.47	−5.59 ***	σ^2	11.16	12.96 ***
$(\ln K_{it})^2$	−6.14	−10.55 ***	γ	0.93	132.64 ***
t^2	−0.02	−1.08	LLF	−677.92	
$\ln K_{it} \ln L_{it}$	0.00	4.06 ***	LR	1560.36	
$t \ln K_{it}$	0.11	5.25 ***		−	
$t \ln L_{it}$	−0.12	−3.57 ***		−	

Note: *, **, and *** indicate that the estimated results are significant at the 1%, 5%, and 10% levels, respectively.

It can be seen in Table 5 that the two major investments in technological innovation (personnel and fund investments) both have a significant negative impact on the technological innovation efficiency of new Chinese energy enterprises at the 1% level. This indicates that the personnel and fund investments in R&D did not stimulate the technological innovation efficiency, which agrees with the findings of Chen et al. [28]. The main reason is that China's energy industry mainly relied on the increase in production factors rather than technological progress in the past, which resulted in a shortage of high-end R&D talents when tackling bottleneck problems. It is difficult to improve the technological innovation efficiency only by increasing the number of R&D personnel, and therefore enterprises should focus on quality rather than quantity in recruiting talents and establish a sound and stimulating mechanism for cultivating talents. Meanwhile, enough funding is a necessity for carrying out technological innovation, but currently new Chinese energy enterprises often prioritize large-scale production over innovation. The inadequate investment in R&D makes it difficult to meet the needs of further technological innovation and can even lead to a higher probability of R&D failure. In addition, some enterprises may prefer to imitate others, but increasing R&D investment in this way cannot really improve its own technological innovation and stimulate its development. Therefore, new Chinese energy enterprises should make their own development strategies, target the forefront of technology in the key fields, recruit and cultivate outstanding talents, and strictly control innovation funds, so as to utilize their R&D funds efficiently.

According to the model setting in this paper, if the estimated coefficient of the technical inefficiency term is positive, it indicates that this factor has a negative impact on

technological innovation efficiency, and if the estimated coefficient is negative, its impact on technological innovation efficiency is positive. In terms of technical inefficiency terms, the estimated coefficients of enterprise profit and government support are -0.06 and -1.06 , and they are significant at the 10% and 1% confidence levels, respectively, indicating that the above two factors have a significant positive impact on technological innovation efficiency, which is consistent with the findings of Lin et al. [76] on wind power enterprises. Specifically, when enterprises have more profits, they invest more funds in R&D in the “professionalized, refined, specialized and innovative” fields, which can attract more high-end talents, upgrade their technical equipment, and improve their technological innovation efficiency. Meanwhile, government support can not only provide financial subsidies for new energy enterprises but also provide guidelines for R&D, greatly reducing their innovation risks. However, the estimated coefficient of the proportion of state-owned capital is 0.43 , which is significant at the 5% confidence level, indicating its significant negative impact on technological innovation efficiency. Perhaps the reason is that government support may give certain monopoly benefits and an advantage in “soft budget constraints” to enterprises with a higher ratio of state-owned capital, but it also leads to low enthusiasm for them to improve their technological innovation efficiency, which is similar to the findings of Xia et al. [78] with mining enterprises. In addition, although reasonable supervision by state-owned capital is conducive to regulating the innovation process and reducing ineffective investment, the close political connection between state-owned enterprises and the government may make these enterprises conservative in innovation, which to some extent limits the innovation in the “professionalized, refined, specialized and innovative” fields and is not good for enterprises to break through bottleneck technologies.

The calculation results of the technological innovation efficiency of new Chinese energy enterprises from 2016 to 2021 are shown in Table 6.

Table 6. Technological innovation efficiency of new Chinese energy enterprises.

Category	2016	2017	2018	2019	2020	2021	Mean
All sample enterprises	0.9077	0.9085	0.9108	0.9187	0.9072	0.9041	0.9078
Growing enterprises	0.9095	0.9110	0.9113	0.9182	0.9073	0.9045	0.9086
Mature enterprises	0.9083	0.9084	0.9137	0.9200	0.9081	0.9062	0.9091
Declining enterprises	0.9021	0.9021	0.9040	0.9075	0.9054	0.9051	0.9044

It can be seen in Table 6 that the average technological innovation efficiency of new Chinese energy enterprises fluctuated around 0.90 from 2016 to 2021, indicating their relatively high technological innovation efficiency. This is mainly because the policy documents issued by the Chinese government in recent years, such as the Action Plan for Energy Technology Revolution and Innovation (2016–2030) and the 14th Five-Year Plan for Technological Innovation in the Energy Field, continuously stimulated their R&D and improved their innovation efficiency effectively. Since 2020, their technological innovation efficiency has shown a downward trend, which is mainly due to the impact of COVID-19 on the global energy market. Enterprises had to spend more funds on their routine business activities, which had a crowding-out or substitution effect on R&D investment. The severity of COVID-19 in 2021 was far greater than expected, which resulted in a continuous decline in technological innovation efficiency.

From the perspective of lifecycle stages, the technological innovation efficiency among enterprises is different, and mature energy enterprises have the highest technological innovation efficiency, followed by growing and declining ones, which agrees with the findings of Fang et al. [92]. The main reasons are as follows: mature enterprises have strong development momentum, sufficient financial support, and a high position in the market. At this stage, they have advanced technology and clear R&D directions, and so they can turn their technological innovation achievements into products faster and have the highest technological innovation efficiency, which is consistent with the findings of

Yao et al. [60]. Growing enterprises are in a period of rapid development with a strong will for technological innovation. However, they have insufficient financial and talent reserves, and yet they have to carry out multiple businesses simultaneously. Some growing enterprises did not originally belong to the new energy industry, such as Shanshan Co., Ltd., but in recent years, with favorable policies and changes in the economic situation, they have extended their business into the new energy field. There are definitely industry barriers for them in technological innovation, and so their technological innovation efficiency is lower than that of mature enterprises. The declining enterprises have difficulties such as increased financial risks and cash flow difficulty. At this stage, the essence of their technological innovation is to develop and transfer core competitiveness, and so their technological innovation efficiency is the lowest, which agrees with the findings of Li et al. [63].

5.2. Growth Level of New Chinese Energy Enterprises

An instance analysis was conducted on 81 new energy enterprises in China from 2016 to 2021 based on the growth level evaluation model constructed in Section 3.2, and the specific results are shown in Figure 2.

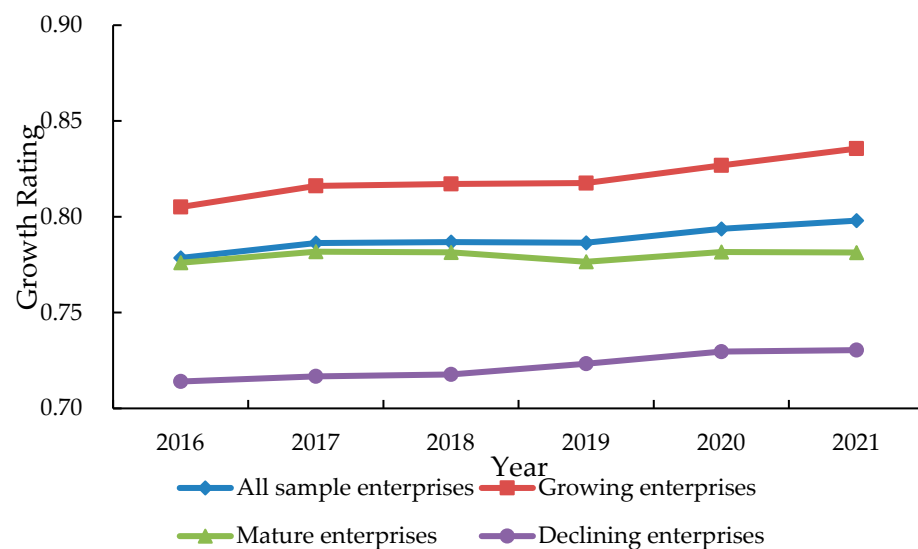


Figure 2. Growth ratings of new, listed Chinese energy companies from 2016 to 2021.

Figure 2 shows an upward trend in the overall growth ratings of new Chinese energy enterprises from 2016 to 2021, with the highest average score of 0.798 in 2021 and the lowest average score of 0.7785 in 2016. This indicates that these enterprises are growing well currently and have great development potential. The main reason is that new energy often contains extremely little carbon or no carbon at all, which meets the demand for low-carbon energy transformation advocated by China's "carbon peaking and carbon neutrality" strategy. In recent years, many incentive policies have been made to promote the development of new energy enterprises, such as the 13th Five-Year Plan for Renewable Energy Development released by the National Development and Reform Commission in 2016. With policy support, these enterprises have entered the "fast lane" of development and achieved outstanding results in wind and solar power generation, with installed capacity ranked among the top in the world and generation costs declining continuously. However, it is worth noting that the overall growth ratings of these enterprises reached a valley value in 2019, and the average value reached 0.7864. This is mainly due to On further Improving the Financial Subsidy for Promoting New Energy Vehicles, a policy document issued by the Chinese Ministry of Finance in March, 2019. The new policy cancelled local subsidies and reduced national subsidies, and this stringent financial policy hindered the development of new energy enterprises in the short term because high operating costs remained a bottleneck for their development, which agrees with the findings of

Pakere et al. [93]. Since 2020, the overall growth ratings have showed an upward trend. This is mainly because, with the implementation of “carbon peaking and carbon neutrality” in China, new energy enterprises, as the vanguard in this strategy, have entered a new era of innovation-driven development, which is consistent with the findings of Yao et al. [94]. However, under the impact of black swan events such as COVID-19, the overall growth rate was relatively slow. Specifically, growing enterprises maintained an accelerated growth momentum, while the growth of mature enterprises and declining enterprises fluctuated, mainly due to the differences in their growth characteristics and strategic orientation. At present, there is still some room for improvement for these enterprises because there are seasonal and regional differences in the use of new energy. In order to achieve “carbon peaking and carbon neutrality”, in the post-epidemic era, these enterprises should try to stimulate their internal innovation mechanisms and improve the flexibility and stability of new energy supplies in different seasons and regions.

From the perspective of lifecycle stages, the overall growth of all the enterprises at different stages showed an upward trend from 2016 to 2021, indicating that their development ability continues to improve and that they have entered a golden stage of healthy development. The ranking of enterprise growth at different stages is as follows: growing stage > mature stage > declining stage. The growth rating of growing enterprises is the highest, with an average value of 0.8197 during the research period, mainly because they are in a period of rapid expansion at this stage. Mature enterprises are at a relatively stable developing stage with a strong overall strength, but they are prone to entering a bottleneck period at this stage since the marginal benefits brought to their development by management and technology will gradually decrease, which agrees with the findings of Ahsan et al. [65]. Whether this predicament can be solved will have a decisive impact on their future development. Therefore, their focus is to seek breakthroughs in technology transformation. Compared to growing enterprises, their development potential is relatively weak, and therefore the growth rating is also relatively low, with an average value of 0.7798 during the research period. Although declining enterprises still have a certain market share because of their early accumulation, their brand influence significantly weakens. It is only possible to achieve a second upswing through disruptive and successful technology transformation and breakthrough, which agrees with the findings of Ahsan et al. [95]. Therefore, the growth rating of declining enterprises is the lowest, with an average value of 0.7220 during the research period.

5.3. Benchmark Regression Results

5.3.1. Direct and Intermediary Effects

By taking the mediating effect into consideration, the direct and intermediary effects of technological innovation efficiency on enterprise growth were empirically analyzed by a fixed effects model. The specific results are listed in Table 7. The first column is the analysis results, based on model M1, take TE as the independent variable and EG as the dependent variable. The second column shows analysis results based on model M2 by taking TE as the independent variable and MS as the dependent variable. The third column depicts analysis results based on model M3 by taking both TE and MS as independent variables and EG as the dependent variable.

The first column shows that the regression coefficient of TE is 0.345 and it passed the significance test at the 1% level. That is, for every 1% increase in TE, EG will increase by 0.345%. It can be concluded that the improvement of TE can not only reduce production costs by optimizing resource allocation, but also can increase economic benefits by improving product quality and developing new products, thereby greatly promoting the growth of new Chinese energy enterprises, which is consistent with the findings of Wang et al. [45]. In this case, hypothesis H1 is validated.

Table 7. Benchmark regression of the impact of technological innovation efficiency on enterprise growth.

Variables	(1)	(2)	(3)
	EG	MS	EG
TE	0.345 ***	0.540 ***	0.174 ***
GOV	0.001 **	0.002 ***	−0.000
LEV	−0.044 ***	−0.044 ***	−0.030 ***
SIZE	0.039 ***	0.045 ***	0.025 ***
AGE	−0.000	0.000	−0.000 ***
EC	−0.000 ***	−0.000 ***	−0.000 ***
MS	−	−	0.316 ***
Constant	−0.393 ***	−0.904 ***	−0.105 ***
F	47.58 ***	69.62 ***	53.49 ***

Note: **, and *** indicate that the estimated results are significant at the 5%, and 10% levels, respectively.

The regression coefficient of GOV, the control variable in the model, is significantly positive at a confidence level of 5%, indicating its positive impact on the growth of new Chinese energy enterprises at the present stage, which agrees with the findings of Jiang et al. [96]. This is mainly because government support, mostly fiscal subsidies, can provide sufficient financial assistance for enterprise growth. At the same time, the government can guide the direction of innovation proactively at the strategic level and assist them in solving problems, such as technical constraints, insufficient funding, and imperfect market mechanisms, which can bring sufficient development space and opportunities to enterprises. The regression coefficient of LEV is significantly negative at a confidence level of 1%, indicating its adverse impact on the growth of new energy enterprises. The reason may be that enterprises cannot fully and reasonably utilize financial leverage at present, which leads to debts and certain financial risks. They may face huge debt burdens under the downward economic situation rendered by the Sino-US trade game and the impact of COVID-19, and their future development will be affected, which agrees with the findings of Fu et al. [97]. The regression coefficient of EC is significantly negative at a confidence level of 1%, indicating that the more concentrated the equity structure, the less conducive it is to a company's growth, which is different from the result of Zhou et al. [84] based on the perspective of green capital. The main reason is that equity is more concentrated on the holding group company in its equity structure and the decision-making power is mainly controlled by minority shareholders. When a conflict of interest arises between them and other shareholders, they tend to make choices in their own favor, which will have a negative impact on the overall interest of the enterprises. Therefore, the development of new energy enterprises in China needs to increase the investment of green capital. The regression coefficient of AGE in model M1 did not pass the significance test, indicating that there is no significant correlation between AGE and businesses' growth, which is different from the result of Pellegrino [83]. The main reason is that new energy industries, as an emerging strategic industry, only started in recent years and most of the enterprises were established between 2016 and 2021, which resulted in relatively low development heterogeneity. The regression coefficient of SIZE is significantly positive at a confidence level of 1%, indicating that the economy of scale does exist in these enterprises. The larger the asset size, the lower the unit production cost, the better the company's rules and regulations, the more sufficient capital reserves, the easier it is to benefit from preferential government policies, and the stronger the ability to withstand market risks, which is consistent with the findings of Liu et al. [98].

The second column shows that TE has a significant positive impact on MS at the 1% confidence level. For every 1% increase in TE, MS will increase by 0.540%. The third column shows that after adding mediating variables, both MS and TE have a significant positive impact on EG at a confidence level of 1%. For every 1% increase in MS and TE, EG will increase by 0.316% and 0.174%, respectively. This indicates that the improvement of technological innovation efficiency can effectively expand an enterprise's market shares

and bring huge development space and competitive advantages, which is consistent with the findings of Liu et al. [99]. MS plays a mediating role between TE and EG. Technological innovation can quickly expand a company's market shares and safeguard and support their development. As the world's largest new energy market, China has gradually increased its share in the global market in the past few years due to its technological advancements in fields such as photovoltaic solar energy, lithium batteries, and new energy vehicles and brought massive development potential to new energy enterprises. In summary, improving the technological innovation efficiency can have a significant, positive stimulating effect on the growth of new Chinese energy enterprises through expanding market share. Hypothesis H2 is validated.

5.3.2. Heterogeneity Effect

Based on the lifecycle division results of the sample enterprises, the heterogeneity effects of technological innovation efficiency on enterprise growth at different stages were analyzed. The specific results are shown in Table 8.

Table 8. Heterogeneity effects at different lifecycle stages.

Variables	Growing Stage	Mature Stage	Declining Stage
TE	1.282 ***	0.274 *	−0.811 **
GOV	0.007	0.007 ***	0.015 **
LEV	−0.033	−0.112 ***	−0.192 ***
SIZE	0.028 ***	0.032 ***	0.058 ***
AGE	−0.000	0.001 *	−0.003 **
EC	−0.001 ***	−0.001 ***	0.001
Constant	−0.705 ***	−0.791 ***	−1.417 ***
F	13.04 ***	52.39 ***	19.23 ***

Note: *, **, and *** indicate that the estimated results are significant at the 1%, 5%, and 10% levels, respectively.

According to Table 8, the regression coefficients of TE for growing, mature, and declining enterprises are 1.282, 0.274, and −0.811, respectively, which are significant at the confidence levels of 1%, 10%, and 5%, respectively. This indicates that for both growing and mature enterprises, TE has a significant positive impact on companies' growth, and improving technological innovation efficiency will greatly promote their development, which agrees with the findings of Chen et al. [100]. For declining enterprises, TE has a significant negative impact on their growth, and trying to improve their TE blindly will actually hinder their development to a certain extent. Hypotheses H3a, H3b, and H3d are all validated. At the same time, the regression coefficient of TE in growing enterprises is 1.282, which is much greater than 0.274 in mature enterprises, indicating a significantly greater driving effect of TE on EG in growing enterprises than in mature enterprises. Hypothesis H3c is validated.

The new energy industry is a capital-intensive and long-cycle industry. As for growing enterprises, their scale and market reputation are relatively small, and their business is in a critical period of rapid development. Based on the accumulation of technology, funds, and resources at the start-up stage, they are developing more patents and accelerating the upgrading and iteration of their products. At this point, the improvement of technological innovation efficiency can fully utilize their funds and help them quickly gain development space in the market. With their outstanding advantages in products and costs, they can take the lead in the segment markets, stand firmly in fierce competition, and heighten entry barriers. Therefore, the positive driving effect of technological innovation efficiency on their growth is the most significant, which agrees with the findings of Deligianni et al. [101]. At present, growing enterprises account for a large proportion in new Chinese energy enterprises. In order to seize the opportunity to achieve "overtaking by lane-changing", it is urgent to upgrade technology, expand international markets, create international

brands with Chinese characteristics, and make them a new engine in driving China's economic growth.

At the mature stage, enterprises are at the peak of development with the strongest profitability in the whole lifecycle, so have strong ability to bear the risk of possible innovation failure. For example, photovoltaic power, a focus in the Chinese capital market, has become quite cheap and can make profits without government subsidies because it has the same or even higher cost-effectiveness compared to other power generation methods [96]. Mature enterprises boast advanced technological equipment, clear R&D directions, and accumulated management experience. Therefore, the improvement of technological innovation efficiency at this stage will have a positive impact on their growth. However, it is worth noting that, faced with more complex supply and demand in the market, more intense competition, and more technology challenges, their focus is gradually shifting towards internal and external management, such as market expansion and product structure adjustment, and towards differentiated products and minimized marginal costs. Therefore, the growth speed brought by improving technological innovation efficiency is not as fast as that of growing enterprises, which agrees with the findings of Haiyan et al. [66].

Declining enterprises have low technological innovation efficiency and a poor ability to achieve transformation. They urgently need to carry out high-dimensional and disruptive technological innovation to change their original products completely. To achieve this goal, it takes a huge amount of funds to buy advanced equipment. However, many declining enterprises usually face financial crises, and some of them focus on their business operations and adjusting their internal structure and try to maintain their business by depending on their original fund accumulation and reducing costs simultaneously. Some other companies still choose to increase investment in R&D in order to find new growth points so that they can survive and develop again through the compensation effects of innovation [102]. However, in harsh competition, the profit brought by technological innovation may not make up for the high cost of introducing advanced technology and equipment, which can bring them more serious problems and accelerate their decline. In this case, the improvement of technological innovation efficiency actually has a negative impact on their growth, which extends the previous research that did not consider the lifecycle perspective [49–51]. In summary, the impact of technological innovation on enterprises at different lifecycle stages follows a chain evolution process: technology driving (product upgrading, multi-product strategy) → management driving (marketing, cost management), → innovation driving (disruptive innovation, transformation).

6. Conclusions and Policy Suggestions

6.1. Conclusions

This research selected panel data from 81 new, listed energy companies in China from 2016 to 2021 as the research object, and examined the heterogeneous effects of technological innovation efficiency on enterprise growth from the perspective of lifecycles. The main research conclusions are as follows: (1) Due to favorable policies, the technological innovation efficiency of new Chinese energy enterprises currently fluctuates around 0.90, which is a relatively high level. The ranking of technological innovation efficiency at different lifecycle stages is mature enterprises > growing enterprises > declining enterprises. (2) Growing enterprises are in a period of rapid expansion, and therefore their growth ratings are the highest. The marginal benefits of management and technology gradually decrease in mature enterprises, resulting in lower ratings than those of growing enterprises. Declining enterprises have the lowest growth ratings, and so there is an urgent need for them to explore the second curve of development. (3) Technological innovation efficiency has a significant positive impact on the growth of enterprises, and market share plays a mediating role in this process. Among them, government support and asset size have a positive impact, while financial leverage and equity concentration have a negative impact, and the impact of establishment years is not significant. (4) Technological innovation efficiency also exhibits a differentiated effect on enterprises at different stages, following a chain evolution

process: technology driving (product upgrading, multi-product strategy) → management driving (marketing, cost management) → innovation driving (disruptive innovation, transformation). Specifically, technological innovation efficiency has significant positive impacts on both growing and mature enterprises, and it has more impact on growing enterprises under the demand for innovation-driven development. Declining enterprises often face difficulties such as unstable operating conditions and outdated technological equipment, and unreasonable technological innovation may actually accelerate their decline.

6.2. Policy Suggestions

Based on the research findings, the following policy suggestions are proposed:

- (1) Considering the heterogeneity effect of technological innovation efficiency on the growth of new energy enterprises at different lifecycle stages, the Chinese government should implement differentiated strategies according to the development characteristics of different enterprises. Growing enterprises should endeavor to develop their technology steadily, ensure the successful implementation of their R&D plans, reduce the probability of R&D failures, consolidate the foundation of technological innovation, create core competitiveness, and seize the market ahead of other competitors. Mature enterprises should maintain their advantage in technology, increase their investment in R&D, target the most advanced technology in the world, and develop “professionalized, refined, specialized and innovative” technologies in the industry so as to continuously improve their competitiveness in products and services and expand their international market while maintaining the domestic market. They should also explore new growth points and strengthen their comprehensive capabilities with advanced technology and excellent product quality. Declining enterprises should evaluate their own development situations scientifically and objectively and choose development strategies cautiously. They should choose cautiously to develop core technologies to seek new profit growth points and avoid blind and resource-wasting R&D activities, so as to lengthen their lifecycles or even create a new lifecycle.
- (2) New Chinese energy enterprises should attach importance to the economy of scale, increase investment in innovative resources, and achieve large-scale development. They should recruit and allocate high-end talents reasonably and build a scientific and standardized evaluation mechanism to stimulate the enthusiasm of R&D personnel. They should build a coordinated and complementary relationship between traditional energy and new energy and reduce the costs of various stored energies and flexible resources (such as hydrogen energy) through technological progress to show the value of peak regulation. At the same time, in the context of Industry 4.0, the Chinese government can prioritize the digital transformation of new energy enterprises and integrate physical systems of power generation with digital technology by using big data and cloud computing. In addition, when formulating innovation policies, greater support should be given to western areas and non-state-owned enterprises.
- (3) Whether new energy enterprises choose technology innovation has a great relationship with their own input costs and benefits. Firstly, the government should accurately implement financial support policies and give priority to tax incentives in key sectors such as research and development and technology transformation. Secondly, it can improve the risk compensation and risk diversification mechanism of credit businesses and expand external green financing channels for new Chinese energy enterprises by establishing a multidimensional financial system that supports independent technological innovation. Thirdly, it is necessary to guide the establishment of high-tech industry clusters and industry parks for new energy enterprises and encourage the construction of technological information-sharing platforms between universities, research institutes, and new energy enterprises. In addition, enterprises should pay attention to regional location advantages and resource endowment advantages when formulating and implementing their own innovation strategies.

6.3. Study Limitations and Future Research

First, limited by the availability of data, this article mainly selects 81 new energy companies listed in China as the research objects; in the future, the sample range can be expanded to the whole Asian region. Moreover, future research can consider combining DEA theory with the spatial econometric analysis model to more comprehensively investigate the influence mode and regional heterogeneity of technological innovation efficiency on the growth of new energy enterprises.

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