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Analysis on Stochastic Change Characteristics of Technological Innovation Efficiency under Endogenous Change in Technological Information and Investment of Knowledge Capital

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Abstract: The allocation of innovation-related elements is influenced by intangible elements such as technological information, which affects knowledge capital, human capital, and material element investment, resulting in the stochastic change of technological innovation efficiency. The endogenous change in technological information in element investment reduces friction, lowers costs, improves efficiency, and gradually reduces the deviation between knowledge capital investment and technological innovation efficiency. In terms of small knowledge capital investment characterized by the low demand for technological information and a single source, it is easier to make more-accurate predictions, so the stochastic change in technological innovation efficiency tends to be gentle. The endogenous change in technological information continuously increases the proportion of replacing other elements with knowledge capital investment, and the efficiency of technological innovation improves steadily. Under the condition of unchanged investment in other elements, there is a great difference in the duration of technological information between the simultaneous selection and the successive selection of knowledge capital investment. When one-time instantaneous information and continuous complete information are respectively acquired, the stochastic variation of technological innovation efficiency is obvious. On the basis of the technological innovation data of 287 listed companies in eight industries, this paper compares and analyzes the measurement results of GMM and OLS to verify the above findings.

Keywords: technological information; endogenous change; technological innovation efficiency; stochastic change characteristics

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1. Introduction

At present, China is actively building a national scientific and technological governance system, improving the mechanism for science and technology evaluation, and highlighting the achievements, performance, and contributions during the assessment [1]. To evaluate the input–output performance in the field of technology research and development, it is necessary to deepen the research on the internal technical and economic relationship between knowledge capital investment and technological innovation efficiency, mine technological information, and compare and analyze the impact path and degree of their endogenous change on the stochastic change of technological innovation efficiency [2]. Endogenous change in technological information refers to the diversity of technological information between individual subjects after the generation of technological information. However, the technological information in the market is heterogeneous. The established technical achievements can continuously obtain more technological information, and the technological information successively generated is complementary and compatible and coexists with one another. In the process of technological progress, new technological

information is created after continuous agglomeration, reproduction, exchange, synthesis, further utilization, processing, and innovation. In this way, the existing form, value, property rights, and attributes of technological information have become endogenous factors for output increase and efficiency improvement. Market-shared information and private information is constantly synthesized, diffused, superimposed, and collected [3].

Through continuous access to complete technological information, endogenous change in technological information aligns knowledge capital investment more with the allocation of innovation-related elements, improves the level of accurate matching, and optimizes the input–output relationship of innovation-related elements, to significantly enhance the efficiency of technological innovation [4]. However, the reliance on knowledge capital investment generates changeable and perishable characteristics, so that the technological information and efficiency of technological innovation do not change in a one-dimensional linear trend. They do not maintain the same change trend [5]. The allocation share and substitution coefficient of innovation-related elements are affected directly by the change in technological information, and they lead to the uncertain effect of knowledge capital investment on the technological innovation efficiency of material element investment and human capital investment, resulting in stochastic characteristics in the process of endogenous change in technological information [6]. Therefore, mining and discovering more-complete technological information aim to realize the full and intensive utilization of innovation-related elements, optimize the allocation of elements, and improve the efficiency of technological innovation.

However, theoretically, there are still many problems to be further studied. They are as follows. What is the technical and economic relationship between the endogenous change in technological information, the investment of knowledge capital, and the improvement of technological innovation efficiency? How do we infer and judge the changing trend of technological innovation efficiency by comparing and analyzing the endogenous change in technological information? What is the impact of small knowledge capital investment on the endogenous change in technological information, and is it possible to gradually enhance the accuracy of element allocation? When the endogenous change in technological information gradually becomes gentler, the stochastic change in technological innovation efficiency gradually reduces its deviation from the optimal state. Is it feasible to deepen the endogenous change in technological information through the continuous use of technological achievements, and how does the endogenous change in technological information affect the investment of knowledge capital and further lead to the stochastic change characteristics of technological innovation efficiency so as to continuously and steadily improve the efficiency of technological innovation? These theoretical problems can deepen the research on the endogenous change in technological information in innovation activities and help identify the formation and influence degree of stochastic change in technological innovation efficiency, thus providing a reference for the objective analysis and evaluation of the performance and contribution of technological innovation achievements.

The foci of this paper are to include the indicators reflecting the change in technological information in different periods into endogenous explanatory variables and to analyze how knowledge capital investment leads to the stochastic change in technological innovation efficiency. Knowledge capital investment is affected by the endogenous change in technological information in the process of technological progress. The allocation share and substitution coefficient of innovation-related elements uncertainly change. Under the condition of complete technological information, the return to scale of knowledge capital investment is progressively increasing. The input of a unit of knowledge capital and other innovation-related elements will bring a larger share of output growth, the output level will steadily ascend, and the efficiency of technological innovation will continue to smoothly increase. The originalities of this paper lie in its construction of a transmission mechanism of endogenous change in technological information regarding the relationship between the investment of knowledge capital and the stochastic change in the efficiency of technological innovation and its analysis of how this endogenous change brings the stochastic change

effect to the efficiency of technological innovation. This paper studies how the allocation share of knowledge capital and the substitution coefficient of other elements are affected by the endogenous change in technological information, resulting in a large fluctuation in the efficiency of technological innovation. Another creative point of the study is that there is a strict corresponding relationship between optimal technological innovation efficiency and endogenous change in technological information. The optimal technological innovation efficiency is based on complete technological information, while the acquisition of complete technological information does not necessarily contribute to the optimal technological innovation efficiency, because influencing factors such as element allocation, market mechanisms, and the transformation of technological achievements should be also considered. The continuous use of technological information can significantly improve the proportion of innovation-related element allocation, fully excavate and identify the endogenous change in technological information in the allocation of innovation-related elements, and make efficient and intensive use of elements. The regression GMM is adopted in this paper, and the regression disturbance term represents the fluctuation range of technological innovation efficiency. The effect of the change in technological information on the change in R&D output and technological innovation efficiency is studied. Methods such as GMM are used to compare and analyze the results of the changes in the relevant indicators of technological information in different periods and the relationship between them and the element substitution coefficient, further identifying the root causes for the endogenous change in technological information and the stochastic changes in both knowledge capital investment and innovation efficiency.

2. Literature Review

2.1. Changes in Technological Information, Knowledge Capital Investment, and Technological Innovation Efficiency

The higher quality of technological information disclosed by innovation entities means a lower degree of passive deviation between supply and demand. The endogenous change in technological information remarkably affects the change in input–output efficiency (Yang Zhiqiang et al., 2020) [7]. In different target markets, cross-border ecommerce entities implement differentiated technological information strategies (MA Shuzhong et al., 2020) [8]. Nonfinancial information, such as technological information, reflects the internal value of enterprises, and demanders should have such capabilities as search, interpretation, and analysis (Lian Lishuai et al., 2019) [9]. Technological information is an intermediary variable that affects the respective structures of knowledge capital, human capital, and other elements (Li Li et al., 2014) [10]. The sharing of technological information by innovation entities in different environments, such as third-party social networks, personal social networks, and general social networks, has a different impact on the efficiency of capital input and capital output (Liu Gang et al., 2021) [11]. The above literature has focused on how technological information affects the input–output efficiency of innovation-related elements and optimizes the structure and allocation proportion of innovation-related elements. Differentiated technological information strategies and the ability to obtain technological information directly influence input–output efficiency. Relevant research can also deeply analyze how technological information affects the input of knowledge capital, can fully tap the potential of knowledge capital output, and can achieve a more optimized efficiency for technological innovation.

2.2. Duality and Dynamic Change in Technological Information

Innovation entities improve their ability to obtain and interpret technological information, significantly reduce information asymmetry, accurately predict market surplus, and optimize market efficiency (Ding Hui et al., 2018) [12]. The supply and demand network of innovative achievements makes technological information have a dual nature and realizes the unification of information and technology. Technological information is no longer a virtual existence but instead a result of continuous innovation (Zhang Yonglin, 2016) [13]. Infor-

mation asymmetry affects investment costs, generates financing constraints, and intensifies the investment–cash flow sensitivity with irregular change (Qu Wenzhou et al., 2011) [14]. Margin trading will also affect the choice of technological information (Li Zhisheng et al., 2017) [15]. The above research has focused on the identification of, interpretation of, existing forms of, and dynamic changes in technological information and on the interaction between investment and financing. Relevant researchers may further analyze how the endogenous change in technological information affects the allocation share and substitution coefficient of knowledge capital and how to continuously optimize the efficiency of technological innovation by using the endogenous change in technological information.

2.3. Technological Information Promotes the Continuous Utilization of Achievements and Optimizes the Allocation of Elements

T. G. Lewis (2000) defined the information technology revolution since the 1990s, especially the application of informatization, as a friction-free economy [16]. In general equilibrium analysis, information is regarded as an exogenous factor and is not included in decision variables and optimal choices of subject behavior. Zhang Yonglin et al. (2011) explored the internal relationship between the information agglomeration effect and transaction efficiency by using a dynamic game method; studied information endogeneity and agglomeration from transaction behavior; proposed the internal mechanisms with respect to the information agglomeration effect, transaction costs, and economies of scale; and put forward views on market information production, supply, and demand [17]. By continuously using technological achievements to convert information into time and incorporating information elements into the endogenous analysis on the basis of the internal relationship between time and monetary income, we can transform and break through the difficulties for the quantification and marginal analysis of economic factors, such as information and uncertainty, and build an economic model of time-based replication (Zhang Yonglin, 2014) [3].

2.4. Introduction of Technological Information into Endogenous Analysis and Research

On the basis of using game theory thinking, this paper studies the behavior and resource allocation efficiency of an Internet-economy-oriented society from the perspective of physical resources and, in particular, takes information and the Internet as important elements of economic behavior (Elchanan Mossel et al., 2015) [18]. The method of game theory is used to study the Internet and resource allocation from the perspective of information (Yann Bramoulle et al., 2014) [19]. Wolitzky (2013) focuses on the Internet, endogenous change in technological information, market and cooperation, etc., and takes the Internet as an information structure. The change in technological information generates behavior signals in subjects, such that the Internet, information, and behavior are organically connected [20]. Katz and Shapiro (1985) explored information externality, competition, and compatibility from the perspective of subject behavior [21]. Scholars (Marco Battaglini, et al., 2008; Qiuqi Wang, et al., 2019) also comprehensively use game theory and modern financial theory to study market efficiency by taking information as a public resource [22,23].

2.5. Research Paradigm of Information Variables in Economic Activities

Stiglitz and many other scholars around the world have proposed the information paradigm of economics, and they clearly put forward information economics for the first time in 1961 [24]. Its fundamental epistemology is a view on endogeneity (adverse selection, principal agent, and incentive mechanism design theory) [25]. Arrow (1962) first introduced information into mainstream economic analysis, connecting information, uncertainty, and economic activities [26]. In terms of the second peak of information economics, Stiglitz and Vickrey et al. studied information and market efficiency, especially information asymmetry and market incompleteness, and created the modern imperfect market theory and economic analysis. Since the 1960s and 1970s, more scholars have studied the real, imperfect market economy and identified the relationship between information and market structure. More-

over, studies on information acquisition (Schmitz, 2006) [27], the aggregation of market information (Amato, Shin h s. 2006; Lawrence Choo, et al., 2019) [28,29], the social value of information (Farrell, 2007) [30], and information and market organization (Dixit, 2009) [31] helped people gain a better understanding. These scholars regarded information as a given exogenous factor for research.

3. Theoretical Analysis and Framework

3.1. Analysis of Endogenous Change in Technological Information and Knowledge Capital Investment

In the process of knowledge capital investment, it is difficult to quantify and conduct a marginal analysis of technological information because of its nonexclusivity, its indivisibility, and the uncertainty of its transaction value. The endogenous change in technological information is the deviation between the change expectation before technological progress and the actual result of technological progress. The influence degree of this endogenous change can be analyzed by comparing different variables. The smaller deviation between the advanced prediction of technological progress and the actual results will mean a better fit between the endogenous change in technological information and the need of knowledge capital investment. Various innovation-related elements provide complete technological information, and the allocation of elements is optimized. In contrast, when the deviation between the two is greater, the endogenous change is less obvious, and the role of technological information in knowledge capital investment is not sufficient. The endogenous change in technological information occurs in the probability set of continuous technological progress. The change in relative distance between two technological progress probabilities is caused mainly by incomplete technological information. When the frequency and range of changes in technological information are greater, more-complete technological information will be obtained after testing and screening; the production process will make full use of the investment in knowledge capital; and the output value of new products will be significantly increased, thereby remarkably improving the efficiency of technological innovation.

The endogenous change in technological information accelerates the investment in knowledge capital and helps absorb more-relevant elements into efficient production processes. Under the condition of no increase in the input costs of technological achievements and knowledge capital, a significant increase in innovation output is realized at the input costs of a few relevant elements. The endogenous change in technological information causes a profound efficiency improvement in the allocation of innovation-related elements, which makes the innovation-related elements in the form of knowledge and the tangible material elements highly complementary, compatible, and open. In the processes of knowledge capital investment and element identification, flow, and matching, the endogenous change in technological information can reduce friction, lower costs, and improve efficiency. It realizes complete transfer and change in the form of property rights, value, and utility, and it generates inseparable new technological information with attributes such as replicability, sharing, and public goods. Its result produces positive externalities.

With the continuous use of technological information, the knowledge capital investment has been repeatedly used, which has a significant scale effect, leads to a great reduction in the unit output cost, and results in a significant improvement in the efficiency of technological innovation. It depends on the perception, application, and transformation of knowledge-type and information-type achievements in the production process. The endogenous change in technological information optimizes the allocation of innovation-related elements and improves the output level of given investments. It occurs mainly in processes such as the expectation for purchasing results, selection, the probability and judgment of technological progress, the supply–demand mechanism, the degree of depreciation and compensation, returns on investment, etc. The intermediary role of the endogenous change in technological information in the process of knowledge capital investment refers to the change in element allocation share, the substitution rate, and the continuous utilization

of innovation-related elements, accelerated depreciation, etc. This will help improve the respective input structures of knowledge capital and other innovation-related elements, optimize the allocation proportion, and avoid the dissipation and loss of innovation-related elements. Because the endogenous change in technological information has no spatial constraints, the repeated utilization of technological information can expand the space-time scope of element allocation. Thus, Hypothesis 1 is proposed as follows.

Hypothesis 1. *The endogenous change in technological information, which is different from independent tangible elements, can reduce friction, decrease costs, and improve efficiency in the process of inputting innovation-related elements, thus gradually reducing the deviation between the change trends of knowledge capital investment and technological innovation efficiency.*

3.2. Analysis of the Relation between the Endogenous Change in Technological Information and Innovation Output

The endogenous change in technological information reflects a set of technological achievements and is closely related to the input and output of relevant innovation-related elements. Without exclusivity, it is a change process full of multiplicity and diversity. A sharp increase in the endogenous change in technological information will contribute to the intensive utilization of innovation-related elements and the repeated use of technological achievements, and it will further significantly improve the output level. Additionally, in terms of the output of knowledge capital investment, the output level changes not in a linear pattern thanks to the influence of factors such as technology source, the transaction of achievements, the allocation and transformation of innovation-related elements, etc. Expanding the scale of knowledge capital investment will not produce an equivalent output increment, and the change in the efficiency of technological innovation is uncertain [32]. Detailed analyses of the endogenous change in technological information can help deeply study the change trends of knowledge capital investment and technological innovation efficiency and identify the reasons for the formation of the deviation between them, to more accurately measure the degree of this deviation. In addition, it can reveal the movement and change characteristics of technological information, and the value of technological information in market transactions can be more accurately reflected by two aspects: the rising R&D expenditure of suppliers and the output and income of users. After the characteristics of changes in technological information have been compared and analyzed, the results show that the changes are uncertain and can be repeatedly copied. The ownership return mechanism can be clearly subdivided.

In the process of the input and output of knowledge capital, the endogenous change in technological information promotes the intensive and efficient use of innovation-related elements. Knowledge capital investments such as knowledge, technology, and information can rapidly increase the level of output. However, affected by incomplete technological information, the level of output is lower than the highest level. There are many stochastic interference factors. Increasing one unit of knowledge capital investment will not necessarily bring one unit of innovation output. The endogenous change in technological information can effectively absorb and remove these stochastic factors. In the process of continuous technological progress, a large amount of new technological information is gradually accumulated with technological updating and substitution. At the same time, new technological information is derived.

The endogenous change in technological information gives the input of innovation-related elements a feature of increasing returns to scale, contributing to the continuous and repeated use of technological information and the expansion of the space-time scope for the allocation of innovation-related elements. When two innovation-related elements to a certain extent match in the allocation process, there will be an exchange between two groups of technological information sets, leading to a rise in the output level. Technological information sets are attached to technical scheme R&D, implementation, achievements, pa-

rameters, etc. The value of technological information determines the value of the exchanged innovation-related elements, which is reflected mainly by the level of innovation output.

Within a small range of endogenous change in technological information, the continuous and repeated use of knowledge capital investment will also bring about sharp fluctuations in the level of output. Moreover, the form of endogenous change is not unique, resulting in much-subdivided information. Through the replication and diffusion of innovative information, complete technological information is gradually obtained. The corresponding technological innovation efficiency reaches an optimal level from a low level.

In the allocation of innovation-related elements, the technological information owned by the knowledge capital supplier and the demander is asymmetric. The information on the knowledge capital investment of the supplier is communicated to the demander, which has a great impact on its output level. There are great differences between the two sides in the role and effect of endogenous changes in technological information. Technological information comes from the supplier of knowledge capital. It has complete and correct technological information in terms of technical performance, efficiency, configuration, and upgrading potential. The technological information owned by the demander of knowledge capital directly affects the output level of knowledge capital, including element allocation conditions, technical and economic conditions, income expectations, etc. As the endogenous change in technological information deepens, both the supplier and demander of knowledge capital will gradually obtain more-complete technological information, thus optimizing the allocation of innovation-related elements and significantly improving the efficiency of technological innovation. Therefore, Hypothesis 2 is proposed as follows.

Hypothesis 2. *The endogenous change in technological information makes innovation output come from the repeated use of innovation-related elements and gradually eliminates stochastic interference factors, to achieve higher innovation output with lower knowledge capital investment.*

3.3. Analysis of the Correlation between the Endogenous Change in Technological Information and the Share of Knowledge Capital Investment

In the case of a small share of knowledge capital investment, the endogenous change in technological information is affected by fewer interference factors, the source channels of technological information are limited, the information stock is low, and the share and structural proportion of element allocation is relatively stable. Technological information is fully identified and transformed, and the range of change is relatively stable. When technological information is repeatedly used for production, the knowledge capital investment on a given scale is perfectly combined with enormous innovation-related elements and penetrates tangible elements, leading to the output of new products. There is no waste, and the output potential of technological information in knowledge capital investment has been deeply tapped. Compared with a large share of material element investment and knowledge capital investment, this combination enables material elements to accurately absorb the innovation-related elements in the form of knowledge and put relevant innovation-related elements into production to a maximum level, resulting in the highest output level and the optimal state of technological innovation efficiency.

For a small share of knowledge capital investment, the allocation of innovation-related elements faces a relatively lower demand for technological information and has an insignificant effect on the output level and technological innovation efficiency. The input–output scale of innovation-related elements is relatively smaller. The technological achievements introduced and available for selection are not adequate. There is limited potential for the in-depth mining, absorption, and utilization of technological information. In terms of the transmission of demand for technological information, technological information is fully transmitted from the owner to the production process, and there is no dissipation or overflow of technological information. Furthermore, the endogenous change in technological information leads to a small share of knowledge capital investment to completely penetrate

material elements. The limited selectivity of element allocation enables the greatest use of knowledge capital investment.

Given a small share of knowledge capital investment, the endogenous change in technological information can be more accurately predicted and judged. Technological information is relatively stable in the processes of penetration, identification, absorption, and transformation, and its uncertain change is gentle. The technological information smoothly flows and can be fully identified and absorbed in the production process, achieving zero residual. This endogenous change can be transformed into the conditional probability from cause to result, so as to accurately quantify and analyze the relationship between the change in technological information and knowledge capital investment and further improve the accuracy of prediction. This endogenous change makes the technological information in the allocation of innovation-related elements more transparent, predicts future changes, and obtains complete technological information on input scale, direction, focus, output, etc. The innovation-related elements with a given purpose gain the highest returns in the allocation process, without suffering greater losses from the loss of other possible purposes, and minimize the opportunity cost of knowledge capital investment.

With regard to a small share of knowledge capital investment, the endogenous change in technological information is relatively stable in the different stages of technological progress, and the range of change is small. The technological information contained can predict the gradual change in technological progress. This is because a small share of knowledge capital can promote only insignificant technological progress instead of remarkable technological progress. Hypothesis 3 is proposed as follows.

Hypothesis 3. *In the case of a small share of knowledge capital investment, owing to the limited sources of technological information and obviously lower demand, the endogenous change in technological information can be more accurately predicted in the allocation of innovation-related elements, effectively removing the stochastic change in the efficiency of technological innovation caused by incomplete technological information. Against the step-by-step technological progress, a small share of knowledge capital keeps a relatively stable relationship between human capital, material element investment, and technological innovation efficiency.*

3.4. Endogenous Change in Technological Information and Knowledge Capital Substitution Coefficient

In the allocation of innovation-related elements, the coefficient of substitution of human capital and material element investment with knowledge capital investment reflects the internal technical and economic relationship between them, which is a main sign of endogenous change in technological information. An increase in knowledge capital investment will enhance the output level and technological innovation efficiency, with a high concentration of technological information and rapid updating and change.

The endogenous change in technological information realizes the intensive and efficient use of technological achievements, and it guides the improvement of the substitution coefficient of knowledge capital. A unit of knowledge capital investment can replace the investment of more intermediate products. At a given output level, the continuous use of knowledge capital investment can reduce the costs of innovation-related element investment. After the allocation of innovation-related elements in the current stage, the continuous use of knowledge capital investment helps the extended allocation of elements in other stages. The given knowledge capital investment realizes the continuous allocation in multiple periods and completes the allocation of human capital and material element investment in the same period. The given amount of knowledge capital investment can help gain greater potential for element substitution, and the endogenous change in technological information enables knowledge capital investment to replace both the greater investment of human capital and material elements. During the time extended by the allocation of innovation-related elements and technological information, participants may gain other value. Sufficient and sustainable knowledge capital is offered to participants. The qual-

ity is continuously improved. With gradual technological progress, knowledge capital with higher quality can be obtained, and the allocation of innovation-related elements is optimized, enabling the endogenous change in technological information to significantly improve the output level and technological innovation efficiency.

The endogenous change in technological information is the main influencing factor of the substitution relationship between the investments of knowledge capital, human capital, and material elements, which can fully tap into the potential capacity of existing knowledge capital and technological innovation-related elements and increase output by optimizing the allocation proportion of elements without enhancing the investment of elements. The substitution coefficient of knowledge capital is relatively stable, the input–output ratio of innovation-related elements tends to be optimized, and various elements are fully utilized, without any waste or shortage. A connotation-oriented development path is adopted to avoid the extension of the element investment scale, intensification of the expansion of elements, and reduction in the efficiency of element utilization. The continuous deepening of endogenous change in technological information will bring a greater change to the input–output ratio of innovation-related elements. The efficiency of technological innovation is relatively sensitive to changes in technological information. For every additional unit of knowledge capital investment, the return to scale will increase thanks to the repeated investment and continuous utilization of technological information. Therefore, more human capital and material elements to be input can be replaced, and the input–output ratio will be more optimized. A higher substitution coefficient of knowledge capital will enhance the liquidity of elements and contribute to the acquisition of more-complete technological information in the endogenous change in technological information and the full absorption and transformation of elements, improving the efficiency of technological innovation. Hypothesis 4 is proposed as follows.

Hypothesis 4. *There is an endogenous change in technological information during the allocation of innovation-related elements. The proportion of replacing other elements with one additional unit of knowledge capital investment continuously increases. The given innovation output can be obtained with less investment. The efficiency of technological innovation continuously and steadily rises. When there is no endogenous change in technological information, the proportion of replacing other elements with one additional unit of knowledge capital investment is uncertain, and the output level and technological innovation efficiency change stochastically.*

3.5. Endogenous Change in Technological Information and Optimal Technological Innovation Efficiency

The endogenous change in technological information is incorporated into the expanded knowledge production function. The knowledge capital investment collects more-complete technological information in the processes, such as element acquisition, input, overflow, output, etc., which reflects the characteristics of its endogenous change. Elements are more fully used, and the output level and technological innovation efficiency reach the optimal level, with little fluctuation. For every additional unit of knowledge capital investment, the endogenous change in technological information will lead to a larger proportion of output growth, which is close to the upper limit, and the efficiency of technological innovation will achieve the optimal state. The efficiency improvement caused by the endogenous change in technological information is explained as follows. Technological information can realize the utilization of elements that may create higher value, the corresponding technological achievements can be widely used, and there is relatively great potential for the optimal combination of innovation-related elements and the intensive use of resources. This is because when one unit of knowledge capital investment brings more than one unit of output, the endogenous change in technological information accelerates the connotation-oriented extension of element utilization, technological information is fully identified and absorbed, and elements are fully allocated. The investment of elements such as knowledge capital and technological achievements has an increasing return to scale, which significantly

improves the efficiency of technological innovation. On the contrary, when there is no endogenous change in technological information, much incomplete technological information will inevitably lead to the extensive use of innovation-related elements, thus developing a denotation-oriented extension path. Hypothesis 5 is proposed as follows.

Hypothesis 5. *Increasing the knowledge capital investment will not necessarily enhance the innovation output, and the corresponding technological innovation efficiency does not change in a one-dimensional, linear pattern. The endogenous change in technological information is the main driving factor.*

The endogenous change in technological information plays an important role in the composition of the output value of final products. The allocation of innovation-related elements can absorb a large amount of technological information, transmit it to the output end, and produce more new products. In particular, the investment in new transformative technologies and innovation-related elements enables the efficiency of technological innovation to increase toward the optimal level. At the same time, the increase in the share of new products also depends on the continued use of knowledge capital in the allocation of innovation-related elements. By extending the time for allocation of multiple elements, expanding the selective flexibility of innovation-related elements and technological information, and reducing the unnecessary costs created by the uncertain output after the transformation and utilization of technological achievements, the output efficiency of the investment in new products will increase with the gradual deepening of endogenous change in technological information, which can significantly improve the success probability of the stochastic matching of innovation-related elements. Increasing returns to scale of new product output is achieved by reducing the externalities of innovation-related element allocation and transaction costs.

There are two ways of allocation between knowledge capital, human capital, and material element investment: simultaneous selection and sequential selection. Additionally, there are significant differences in the endogenous change in technological information. In the case of sequential selection, participants always pursue a higher probability of technological progress and collect and absorb more technological information. In a given period, the adoption of the best elements and the most suitable allocation pattern can achieve optimal output efficiency. When the endogenous characteristics of technological information are obvious, it is conducive to the mining, innovation, and transformation of existing technological achievements, and it can create more output to the greatest extent without additional R&D investment. The endogenous change in technological information guides the intensive and efficient use of given innovation-related elements, optimizes the allocation proportion of innovation-related elements, and keeps the element substitution coefficient within a reasonable range, to fully absorb and transform technological achievements and realize the full utilization of technological information. The sequential selection of a variety of innovation-related elements can help collect and absorb more technological information and can greatly improve the probability of technological progress. Knowledge capital can replace more-relevant element investments and enhance the relevance and complementarity of various element configurations, resulting in greater output increment and higher efficiency in technological innovation.

According to the endogenous change in technological information, participants have sufficient time to judge the timing, share and output expectation for the allocation of innovation-related elements, and continuously absorb and repeatedly use technological information according to the output and efficiency improvement goals, so that the endogenous change in technological information meets the need for the intensive use of innovation-related elements. They need to determine what kind of technological information is needed in the dynamic allocation of innovation-related elements and how to improve the input–output ratio. Participants can obtain static technological information only by identifying and utilizing a variety of technological information at a certain time and

failing to fully identify a large amount of dynamic information. The omission of technological information gradually weakens its endogenous nature, making it difficult to achieve the precise matching of various innovation-related elements. There is little room for the continuous utilization of technological achievements. When a variety of innovation-related elements are simultaneously and relatively selected, less technological information is obtained; its endogenous change limits the intensive and efficient use of innovation-related elements. Only instantaneous information can be acquired, and a connotation-oriented development path needs to be developed. Therefore, Hypothesis 6 is proposed as follows.

Hypothesis 6. *The endogenous change in technological information will change the input share and output ratio during the allocation of various innovation-related elements. Under the condition of given human capital and material element investment, there is a great difference in the duration of endogenous change in technological information between the simultaneous selection and the sequential selection of knowledge capital investment. When one-time instantaneous information or continuous complete information is obtained, separately, the characteristics of stochastic change in technological innovation efficiency are obvious.*

4. Data, Indicators, and Manufacturers' Technological Information

The data come from the microdata of listed companies in the Shanghai and Shenzhen stock markets. Specifically, the high-tech industries involve computer equipment, software development, communication transmission, and medical instruments. The capital- and labor-intensive industries include basic machinery, clothing, auto parts, and papermaking. A comparative analysis of such data is made. The composition of indicators is stated as follows: (1) Input indicators refer mainly to the investments in technological innovation of listed companies. The investment in fixed assets reflects the investment in material elements. The compensation payable to employees represents the investment in human capital. The cash expenditure per share for the purchase of intangible assets represents the investment in knowledge capital. (2) Output indicators refer to the earnings per share of the listed companies. (3) Indicators refer to the change in technological information and technological innovation efficiency. The change in technological information is analyzed by comparing the differences between the preinvestment and the postinvestment of intangible assets. The provision for the impairment of intangible assets means the expenditure of intangible assets predicted and judged before investment, while the amortized amount of intangible assets is the actual amortized amount of intangible assets after investment. The ratio of the provision to the amortized amount contains much change in technological information. A lower ratio means the acquisition of less technological information, reflecting more-incomplete technological information. A higher ratio represents the acquisition of more technological information and indicates that there will be more-complete technological information.

According to the industry classification standard of Wanguo Shenyin, there are 287 listed companies in the four high-tech industries and four traditional industries. The statistical description of technological innovation activities and the growth of the main indicators show that technological innovation activities in high-tech industries have great potential for growth, with a continuous and rapid increase in R&D investment and a relatively faster growth of output.

5. Empirical Analysis

5.1. Descriptive Statistics of Technological Innovation Activities

According to Columns (1) and (2) in Table 1, the sample size and observable variables of eight industries reach 287 and 2003, respectively. The samples are representative and chosen from all listed companies in the above industries. Here, 10 indicators are selected from corporate annual reports to study the input–output situation of its innovation-related elements and reflect the status of technological innovation activities. Columns (3)–(5) reflect the variables with knowledge capital included and the intensity of R&D investment, indicating the scope and intensity of knowledge capital investment in technological innovation

activities in various industries. Columns (6), (7), and (8) refer to incomplete technological information, relatively complete technological information, and complete technological information, respectively. Technology-intensive industries involve mainly computer equipment, software development, communication transmission, and medical instruments. The values of the three types of technological information for the four industries are listed as follows: 0.0371, 0.3984, 0.9431, 0.0214, 0.5712, 0.8397, 0.0417, 0.4921, 0.8191, 0.0636, 0.4711, and 0.8019. The investment of human capital and knowledge capital in the four industries has continuously decreased thanks to the gradual acquisition of complete technological information. Complete technological information has a significant substitution effect on the investment of the two innovation-related elements, which is conducive to the full intensive use of human capital and knowledge capital investment. Human capital and knowledge capital are innovation-related elements in the form of knowledge, relying mainly on the leading role of technological information in the allocation of elements. The investments of material elements in the computer equipment industry and communication transmission equipment industry also continuously decreased with the gradual acquisition of complete technological information, which were stated as follows: 2.7276, 1.9498, 1.0476, 1.4558, 1.3034, and 0.5747. With the gradual acquisition of complete technological information, the investments of material elements in the software development industry and in the medical instrument industry showed a changing trend of first decreasing and then increasing and of first increasing and then decreasing, respectively, and related data were as follows: 2.2327, 1.5556, 2.3895, 1.5426, 1.6646, and 0.9363. Because these are highly knowledge- and technology-intensive industries and because material elements are necessary carriers of technological progress and knowledge updating, the dependence on them irregularly changes with the change in technological information. The descriptive statistics show that in the capital- and labor-intensive industries, the investment of the three elements has regularly changed thanks to the gradual acquisition of complete technological information. Affected by the gradual change in technological information, the investment of material elements, human capital, and knowledge capital in the basic machinery industry changed from 1.2977, 1.2030, and 1.0587 to 3.3677, 1.1359, and 1.0417 and finally to 1.5104, 1.1400, 0.8896, respectively, showing a trend of first rising and then falling, first falling and then rising, and continuous declining, respectively. In the capital- and labor- intensive clothing industry, affected by the gradual change in technological information, the investment of material elements has continuously increased as follows: 1.1364, 1.5385, and 2.3747; the investment of human capital and that of knowledge capital have continuously decreased from 1.2306 and 1.5062 to 1.1370 and 0.8895 and to 1.0404 and 0.9896, respectively. In the technology-intensive auto parts industry to an extent, affected by the gradual change in technological information, the investment of material elements and human capital increased from 1.3231 and 1.3249 to 1.6840 and 1.5138 and then decreased to 0.5506 and 0.9665, while the investment of knowledge capital decreased from 1.5062 to 1.1286 and then to 0.9524, which is sensitive to technological information. In the capital- and labor-intensive papermaking industry, the investment of material elements first increased from 0.2936 to 0.3516 and then decreased to 0.0082; the investment of human capital and knowledge capital decreased from 1.2542 and 4.3681 to 1.0051 and 0.8765 and then increased to 1.0355 and 0.9301. The changes in the three elements responding to complete technological information are different and irregular.

Columns (9) and (10) in Table 1 show the changes in innovation output level and technological innovation efficiency. The computer equipment industry and software development industry are knowledge- and technology-intensive industries, with a gradually rising level of innovation output from technological information, while the innovation output level of the communication transmission equipment industry and medical instrument industry continuously declines because of complete technological information. Among the capital- and labor-intensive industries, the innovation output level of the basic machinery industry and clothing industry first rises and then falls because of complete technological information, while the innovation output level of the auto parts industry and papermaking industry first falls and then rises.

Table 1. Descriptive statistics of input–output variables and technical information on technological innovation efficiency.

Industry	Observable Variables	Material Element Investment	Human Capital Investment	Knowledge Capital Investment	Incomplete Technological Information	Relatively Complete Technological Information	Complete Technological Information	Technological Innovation Efficiency	Innovation Output
Computer equipment industry	194	2.7276	1.4786	2.3351	0.0371			3.8802	0.1585
		(9.5286)	(3.2780)	(10.0706)	(0.0676)			(15.22)	(0.4147)
	11	1.9498	1.4548	1.1234		0.3984		9.4777	0.3105
		(2.5114)	(1.0122)	(0.1744)		(0.0683)		(5.1892)	(0.1656)
	5	1.0476	1.2563	0.7879			0.9431	4.7428	0.3138
		(1.1971)	(0.2066)	(0.2948)			(0.0687)	(2.0007)	(0.1455)
Software development industry	477	2.2327	3.8841	2.2829	0.0214			3.3239	0.2138
		(6.5597)	(41.2823)	(7.1399)	(0.0524)			(21.58)	(0.5179)
	34	1.5556	3.0276	1.0599		0.5712		5.5926	0.4976
		(1.8578)	(8.7701)	(0.2796)		(0.2070)		(18.29)	(0.5585)
	10	2.3895	1.1859	1.0244			0.8397	−1.3851	0.5095
		(3.2197)	(0.1804)	(0.1733)			(0.1016)	(31.90)	(0.8238)
Communication transmission industry	139	1.4558	1.2894	1.3873	0.0417			3.9901	0.2408
		(1.7997)	(1.6698)	(1.4110)	(0.0662)			(29.44)	(0.5594)
	22	1.3034	1.1926	0.9947		0.4921		2.424	0.182
		(1.2367)	(0.5395)	(0.2133)		(0.1695)		(9.7404)	(0.4101)
	3	0.5747	0.9232	0.9014			0.8191	−6.9647	−0.0431
		(0.3115)	(0.3249)	(0.0060)			(0.1567)	(14.27)	(0.1352)
Medical instrument industry	108	1.5426	1.989	1.5573	0.0636			8.9679	0.4416
		(2.5618)	(1.1058)	(1.5666)	(0.1252)			(7.4414)	(0.3832)
	26	1.6646	1.634	1.1811		0.4711		5.9696	0.2902
		(1.2149)	(1.2870)	(0.3658)		(0.1180)		(16.59)	(0.6033)
	14	0.9363	1.5417	1.0089			0.8019	4.3044	0.1835
		(0.7336)	(0.7583)	(0.1257)			(0.0819)	(7.8590)	(0.2632)
Basic machinery industry	155	1.2977	1.203	1.0587	0.0268			1.2127	0.1064
		(1.3940)	(0.5023)	(0.2785)	(0.0655)			(32.704)	(0.4937)
	13	3.3677	1.1359	1.0417		0.4668		3.8771	0.1266
		(7.7643)	(0.1954)	(0.3299)		(0.1167)		(18.0201)	(0.3202)
	9	1.5104	1.1400	0.8896			0.8492	−2.9536	−0.0364
		(1.2873)	(0.2166)	(0.1653)			(0.1159)	(12.5541)	(0.3270)
Clothing industry	187	1.1364	1.2306	1.5062	0.0205			1.8644	0.1367
		(0.6026)	(1.3453)	(4.6112)	(0.0444)			(19.3623)	(0.5393)
	4	1.5385	1.137	1.0404		0.3843		6.79	0.2665
		(2.8891)	(0.3162)	(0.1582)		(0.0713)		(3.1340)	(0.1993)
	4	2.3747	0.8895	0.9896			0.8759	−41.28	0.1388
		(86.77)	(0.2654)	(0.0534)			(0.7249)	(93.34)	(0.5505)
Auto parts industry	436	1.3231	1.3249	1.5062	0.0291			4.2439	0.3847
		(1.6800)	(1.5638)	(4.4329)	(0.0663)			(27.87)	(0.6976)
	31	1.684	1.5138	1.1286		0.4068		−35.59	−0.1733
		(1.8550)	(2.3505)	(0.5154)		(0.0802)		(202.80)	(1.4308)
	2	0.5506	0.9665	0.9524			0.9989	4.5475	0.145
		(0.0991)	(0.0046)	(0.0224)			(0.9999)	(5.5600)	(0.1768)
Papermaking industry	114	0.2936	1.2542	4.3681	0.0067			2.2367	0.2178
		0.8120)	(0.9002)	(34.58)	−0.0248			(46.75)	(0.4263)
	2	0.3516	1.0051	0.8765		0.5822		2.8735	0.0441
		(1.8472)	(0.1882)	(0.5153)		(0.0774)		(1.0628)	(0.0156)
	3	0.0082	1.0355	0.9301			0.9261	3.3091	0.0607
		(0.0172)	(0.1257)	(0.0774)			(0.3813)	(1.2447)	(0.0255)

In Table 2, the OLS method is used to conduct a regression analysis on the effect of material elements, human capital, and knowledge capital investment on technological innovation efficiency. By using the GMM, technological information and its corresponding R&D investment are incorporated into endogenous explanatory variables and instrumental variables, respectively, for comparative analysis. Next, the effectiveness of the instrumental variables and regression results are tested. In the GMM regression analysis, the impairment provision and actual amortized amount of intangible assets in the current period and the lagging period are included in the instrumental variables, reflecting the judgment of innovation subjects before the start of technological R&D. The information on technological research and development includes expected income, technology progress probability, R&D cost budget, premium and discount innovation achievements, asset depreciation, etc. The information on the actual amortization of intangible assets includes the compensation for actual R&D expenditure, as well as the time, scale, purpose, main results, transformation effect, and recovery expectation of the expenditure. Technological information covers various processes of R&D activities, such as early investment, medium-term operation, and the returns in a later period, which dynamically reflect the change in technological information. In the knowledge- and technology-intensive industries, thanks to the gradual acquisition of complete technological information, the computer equipment industry, software development industry, communication transmission industry, and medical instrument industry absorb more relatively complete technological information, and the investment of human capital and knowledge capital has a significant effect on the efficiency of technological innovation. According to the OLS method, the contribution of human capital to technological innovation efficiency increased from 1.3082, 0.0048, −8.1277, and −1.6303 to 1.5080, 2.2887, −0.6349, and −0.1023, respectively, and the contribution of knowledge capital investment rose from −0.0918, 0.3804, −5.2729, and −0.2696 to −0.0086, 0.3841, −0.0929, and 1.0354, respectively. Among the capital- and labor-intensive industries, when complete technological information is acquired, the contribution of human capital investment to the growth of technological innovation efficiency decreased from 3.0120, −0.8904, −0.1066, and −0.6094 to 2.1001, 0.6831, −0.7095, and −1.1400, respectively, and the contribution of knowledge capital investment increased from −3.3225, 0.1164, 0.0534, and 1.5005 to 0.3556, 3.5882, 1.2185, and 3.2638, respectively. In the exogeneity test for instrumental variables of the eight industries, the original hypotheses are accepted at the 10% significance level, indicating that the instrumental variables and the explained variables have exogenous characteristics. In the correlation test, the original hypothesis on the communication transmission industry is rejected at the 10% significance level, revealing that the instrumental variables and endogenous explanatory variables are correlative, and the correlation hypotheses of the other seven industries are accepted. Therefore, instrumental variables have high effectiveness. The overidentification test shows that at the 5% significance level, the overidentification hypothesis is rejected for the basic machinery industry, clothing industry, and software development industry, and there is exact identification or insufficient identification. There exists an internal technical and economic relationship between instrumental variables and endogenous explanatory variables and also between endogenous explanatory variables and explained variables. Regarding the other five industries, the overidentification hypothesis is accepted. The three types of technological information encounter difficulty in fully reflecting the technical and economic relationship, and their relationship needs to be more fully explored. In the stochastic change in technological innovation efficiency, relevant results show that when incomplete technological information is gradually transformed into relatively complete technological information and complete technological information, the share of knowledge capital investment changes. By capturing and collecting more-complete technological information, there is great potential for optimizing the output ratio of knowledge capital investment, realizing the continuous and steady improvement of the technological innovation efficiency, and gradually reducing the fluctuation range.

Table 2. Impact analysis and test of technological innovation efficiency with technological information factors.

Industry	OLS			GMM			Overidentification Test		Exogeneity Test		Parameter Test		Minimum Eigenvalue Statistic
	Material Element Input	Human Capital Input	Knowledge Capital Investment	Material Element Investment	Human Capital Investment	Knowledge Capital Investment	$Chi^2(2)$	p	$Chi^2(2)$	p	$Chi^2(3)$	p	
Computer equipment industry	−0.2164 (0.1099)	1.3082 (0.1547)	−0.0918 (0.1114)	0.2354 (0.3465)	0.508 (2.9405)	−0.0086 (0.2404)	1.068	0.059	2.343	0.31	1.22	0.748	0.388
Software development industry	0.6148 (0.1123)	0.0048 (0.0230)	0.3804 (0.1128)	3.4732 (1.7955)	2.2887 (2.0160)	0.3841 (0.8002)	2.606	0.072	0.36	0.836	8.38	0.039	1.587
Communication transmission industry	3.8548 (1.6102)	−8.1277 (1.2593)	−5.2729 (1.4445)	1.9469 (0.9758)	−0.6349 (1.8182)	−0.0929 (9.1122)	0.955	0.021	0.596	0.742	5.22	0.163	0.074
Medical instrument industry	−0.3608 (0.3375)	−1.6303 (0.5091)	−0.2696 (0.4893)	2.4486 (1.3981)	−0.1023 (1.4989)	1.0354 (1.8244)	0.991	0.009	1.975	0.372	6.16	0.104	0.926
Basic machinery industry	1.3106 (0.8924)	3.012 (4.8429)	−3.3225 (4.8089)	3.9184 (2.1706)	2.1001 (5.7721)	0.3556 (9.5892)	1.928	0.382	0.426	0.808	4.94	0.176	0.419
Clothing industry	−0.0069 (0.0070)	0.8904 (0.3725)	0.1164 (0.3724)	0.185 (0.0408)	0.6831 (0.8881)	3.5882 (3.8793)	2.504	0.029	3.056	0.217	45.09	0	0.83
Auto parts industry	1.0532 (1.2765)	−0.1066 (1.2340)	0.0534 (0.6591)	−1.2351 (5.3837)	−0.7095 (1.8199)	1.2185 (13.28)	5.617	0.06	0.694	0.707	0.45	0.931	1.669
Papermaking industry	0.1089 (0.0877)	−0.6094 (1.3160)	1.5005 (1.3188)	−0.8101 (0.1948)	−1.14 (0.6577)	3.2638 (4.1724)	1.115	0.073	1.128	0.569	183.8	0	0.269

The results of the parameter constraint test show that the correlation hypothesis between variables is rejected in the clothing industry and papermaking industry at the 1% significance level, and it is also rejected in the software development industry at the 5% significance level, indicating that the effect of the parameter constraint test is not significant. In contrast, the other give industries pass the parameter constraint test at the 10% significance level. This reveals that the effect of instrumental variables (impairment provision and actual amortization of intangible assets for two consecutive periods) and endogenous explanatory variables (the technological information and knowledge capital investment) on technological innovation efficiency depends mainly on the gradual transformation of incomplete technological information into relatively complete technological information and complete technological information. Mining and absorbing more-complete technological information can help analyze the relationship between the innovation-related element investment and the change in technological innovation efficiency and can further explain the stochastic change in the efficiency of technological innovation.

5.2. Gradual Change in Technological Information and the Elasticity of Substitution among Innovation-Related Elements

The empirical analysis focuses on how the invested human capital and knowledge capital produce a substitution effect in the stochastic change in technological innovation efficiency under the influence of the change in technological information. The elasticity of substitution among innovation-related elements is the main factor affecting the stochastic change in technological innovation efficiency. In Table 3, after the OLS regression of the effect of human capital and knowledge capital on the efficiency of technological innovation, a comparison with the following two cases was conducted: with and without the inclusion of instrumental variables into technological information in the GMM. This comparison aimed to analyze the elasticity of the substitution of the two elements with technological information and its relationship with the efficiency of technological innovation. According to the comparative analysis of Columns (1)–(4) and Columns (7)–(8) in Table 3, in terms of the three regression methods, human capital and knowledge capital in the clothing industry have the same effect on the efficiency of technological innovation, while there is a certain degree of the substitution effect in the other seven industries. With the introduction of technological information into regression analysis, the share of human capital in the software development industry and communication transmission equipment industry during the stochastic change in technological innovation efficiency increased from 0.0154 and −0.573 to 3.0338 and 0.2544 and then decreased to 2.8074 and 0.2236, respectively, while the corresponding knowledge capital showed an opposite trend of change, decreasing from 0.9846 and 7.7525 to 0.4041 and 0.4661 and then increasing to 0.4106 and 0.5829, respectively. Similarly, the share of human capital in the computer equipment industry, auto parts industry, and medical instrument industry decreased from 0.9404, 0.7717, and 1.4187 to 0.4553, 0.3522, and −1.4721 and then increased to 2.8471, 2.0061, and −0.5171, respectively; the share of knowledge capital in the computer equipment industry continuously decreased from 0.0596 to 0.0169 and then to −0.2138; and the share of knowledge capital in the auto parts industry and medical instrument industry increased from 0.2283 and −0.4187 to 0.7208 and 0.2890 and then decreased to −12.0828 and 0.2354, respectively. When the complete technological information is gradually acquired, less knowledge capital investment can make human capital bring greater technological innovation efficiency. The basic machinery industry and papermaking industry are capital- and labor-intensive industries. With the transformation of incomplete technological information into relatively complete technological information and complete technological information, the human capital investment in the basic machinery industry decreased from −1.0451 to −3.0159 and then to −3.2422, and the human capital investment in the papermaking industry decreased from 1.0113 to 0.6955 and then increased to 0.9850. In contrast, the share of knowledge capital in the basic machinery industry decreased from 2.0451 to −0.0384 and then increased to 0.4914, and the share of knowledge capital in the papermaking

industry increased from −0.0113 to 13.1119 and then to 16.8619. The exogeneity test results of the instrumental variables show that the original hypothesis is accepted in the eight industries at the significance level of 10%, indicating that the instrumental variables and the explained variables have exogenous characteristics. Therefore, the instrumental variables have high effectiveness.

5.3. Technological Information and Stochastic Change in Technological Innovation Efficiency

In the empirical research, incomplete technological information, relatively complete technological information, and complete technological information are incorporated into the regression analysis of the effect of material elements, human capital, and knowledge capital investment on the efficiency of technological innovation. The regression disturbance term and the share of the standard deviation of technological information in the expected value of technological information are analyzed to identify the degree of stochastic change in the efficiency of technological innovation caused by the gradual change in technological information. The empirical results show that when incomplete technological information is transformed into relatively complete technological information and complete technological information, the stochastic change range of technological innovation efficiency gradually decreases.

Columns (7) and (8) in Table 4 show that in the case of complete technological information, the stochastic change in the technological innovation efficiency of eight industries is significant. This is because the invested elements in the knowledge- and technology-intensive industries are dominated by the innovation-related elements in the form of knowledge, and technological information is the main carrier to generate the value-added effect during the allocation of innovation-related elements. In the case of incomplete technological information, the innovation-related elements cannot be fully identified, and it is difficult to accurately determine the impact of the quantity and types of innovation-related elements to be allocated and determine allocation timing. There is great uncertainty in the input and output process, and many interference factors exist. As more relatively complete technological information and complete technological information are obtained, the quantity and quality of the invested innovation-related elements better align with the needs of innovation-related element allocation. The given innovation-related elements can be repeatedly used. After the one-time acquisition of technological information, it can play a role in continuously improving the efficiency of technological innovation. The complete technological information is used as a reliance to accurately predict the change in the input–output ratio of innovation-related elements and continuously optimize the allocation of innovation-related elements. In the output process, the complete technological information can help realize the smooth and continuous transformation of innovation-related elements into actual output, reduce the interference of unobservable factors, and avoid fluctuation in the output process. At the same time, complete technological information is also conducive to manufacturers' accurate prediction of the future output level. The weaker influence of stochastic factors and the increase in the output level rely on the full absorption and utilization of technological information and the intensive and efficient use of given innovation-related elements, instead of the consumption of material elements, thus improving the efficiency of technological innovation.

Table 3. Analysis of the substitution elasticity of innovation-related elements for the gradual change in technological information.

Industry	OLS		GMM		Overidentification Test		Exogeneity Test		GMM		Overidentification Test		Exogeneity Test	
	Human Capital Input	Knowledge Capital Investment	Human Capital Investment	Knowledge Capital Investment	$Chi^2(2)$	*p*-Value	$Chi^2(2)$	*p*-Value	Human Capital Input	knowledge Capital Investment	$Chi^2(2)$	*p*-Value	$Chi^2(2)$	*p*-Value
Computer equipment industry	0.9404 (0.1102)	0.0596 (0.1102)	2.8471 (1.8356)	−0.214 (0.1424)	0.0113	0.9153	11.312	0.0233	0.4553 (2.3478)	0.0169 (0.1990)	3.4366	0.0638	0.9782	0.8065
Software development industry	0.0154 (0.0245)	0.9846 (0.0245)	2.8074 (2.0098)	0.4106 (0.4549)	0.5869	0.4436	2.5121	0.6425	3.0338 (2.1112)	0.4041 (0.4582)	0.7571	0.3843	2.3278	0.5072
Communication transmission industry	−0.573 (1.0953)	7.5725 (1.0953)	0.2236 (0.3998)	0.5829 (2.2092)	0.0006	0.9801	2.5986	0.6271	0.2544 (0.4035)	0.4661 (2.1969)	0.0006	0.9811	2.1975	0.5324
Medical instrument industry	1.4187 (0.4692)	−0.419 (0.4692)	−0.517 (0.7753)	0.2354 (1.2018)	0.7152	0.3971	12.095	0.0167	−1.472 (0.7927)	0.2891 (1.1464)	1.1141	0.2912	1.7038	0.6361
Basic machinery industry	−1.045 (4.8876)	2.0451 (4.8870)	−3.242 (2.8923)	0.4914 (7.4951)	0.8964	0.3437	2.8586	0.5818	−3.016 (3.0199)	−0.038 (7.6316)	0.8236	0.3641	2.7511	0.4316
Clothing industry	0.8824 (0.3613)	0.1176 (0.3613)	1.3859 (0.8099)	7.4574 (6.1218)	0.3769	0.5393	4.0655	0.3972	1.1206 (0.8803)	6.6118 (6.0048)	1.2262	0.2682	2.1485	0.5422
Auto parts industry	0.7717 (0.6239)	0.2283 (0.6239)	2.0061 (2.1346)	−12.08 (11.4100)	2.0679	0.1504	1.8882	0.7563	0.3522 (1.9802)	0.7208 (13.8667)	0.2135	0.6441	1.4404	0.6961
Papermaking industry	1.0113 (0.0374)	−0.011 (0.0374)	0.9851 (1.3491)	16.862 (6.7714)	0.6596	0.4504	2.0061	0.7346	0.6955 (1.2628)	13.112 (6.4077)	0.1231	0.7258	1.0475	0.7898

Table 4. Analysis of Technological Information Gradual Change and Stochastic Characteristics of Technological Innovation Efficiency.

Industry	Analysis of Overall Stochastic Characteristics		Stochastic Characteristic Analysis of Incomplete Technological Information		Stochastic Characteristic Analysis of Relatively Complete Technological Information		Stochastic Characteristic Analysis of Complete Technological Information	
	r/E(w)	sd/E(w)	r/E(w)	sd/E(w)	r/E(w)	sd/E(w)	r/E(w)	sd/E(w)
Computer equipment industry	0.8038	0.8581	1.2198	1.2398	0.1649	0.3475	0.0000	0.2095
Software development industry	0.6994	0.7083	0.9370	0.9511	0.4467	0.4645	0.4036	0.4931
Communication transmission industry	0.7358	0.7480	0.6290	0.6260	0.8030	0.8597	0.0000	0.7668
Medical instrument industry	0.5856	0.5921	0.5343	0.5352	0.4906	0.5202	0.1802	0.5087
Basic machinery industry	2.3802	2.3639	0.8881	0.9347	0.3658	0.6703	0.2106	0.8140
Clothing industry	0.4818	1.5332	0.7023	1.0372	0.0000	0.4437	0.0000	1.6273
Auto parts industry	0.7225	0.7269	0.7676	0.7707	0.5734	0.6181	0.0000	0.9199
Papermaking industry	1.2873	0.6818	0.7847	0.8526	0.2008	0.0000	0.2723	0.0000

5.4. Analysis of the Impact of Technological Information on Technological Innovation Efficiency Differentiation

The GMM is used in the empirical analysis. Instrumental variables refer to the impairment provision and the actual amortized amount from intangible assets in the current period and the lagged one period. The shares of knowledge capital investment during the change in technological innovation efficiency are compared and analyzed when technological information is incorporated and not incorporated into endogenous explanatory variables. Columns (3) and (6) in Table 5 show that when technological information is incorporated into endogenous explanatory variables, the share of knowledge capital during the change in technological innovation efficiency in the clothing industry, computer equipment industry, communication transmission industry, medical instrument industry and papermaking industry increases from 1.4042, −0.0326, −0.0551, 0.0081, and 0.5891 to 1.5589, −0.0138, −0.0526, 0.0171, and 0.8042, respectively. This is because when technological information is incorporated into endogenous explanatory variables, knowledge capital can significantly improve the efficiency of technological innovation. The repeated use of a given knowledge capital investment can achieve connotation-oriented development, especially in the capital- and labor-intensive industries, such as clothing and papermaking. The acquisition of complete technological information is the main way to achieve the full, intensive use of innovation-related elements and improve the efficiency of technological innovation.

Table 5. Analysis on the effect of technological innovation efficiency differentiation under the gradual change in technological information.

Industry	With Technological Information			Without Technological Information (Tin = 0)			Sd Test H0:Ratio = 1
	Material Element Investment	Human Capital Investment	Knowledge Capital Investment	Material Element Investment	Human Capital Investment	Knowledge Capital Investment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Computer equipment industry	−0.0083	0.3817	−0.0138	−0.0085	0.3907	−0.0326	0.0484
	(0.0081)	(0.1002)	(0.0081)	(0.0056)	(0.1037)	(0.0085)	
Software development industry	−0.0472	0.0159	0.0139	−0.0472	0.0126	0.0141	0.0013
	(0.0464)	(0.0377)	(0.0217)	(0.0463)	(0.0381)	(0.0217)	
Communication transmission industry	−0.0772	0.0468	−0.0526	−0.0765	0.0467	−0.0551	0.0494
	(0.0355)	(0.0208)	(0.0863)	(0.0356)	(0.0207)	(0.0877)	
Medical instrument industry	−0.0147	−0.0211	0.0171	−0.0191	−0.0487	0.0081	0.0441
	(0.0807)	(0.0747)	(0.1256)	(0.0823)	(0.0691)	(0.1183)	
Basic machinery industry	−0.0112	−0.0823	0.2831	−0.0118	−0.0833	0.2843	0.0499
	(0.0513)	(0.1019)	(0.3312)	(0.0515)	(0.1019)	(0.3316)	
Clothing industry	−0.0041	0.1716	1.5589	−0.0031	0.1597	1.4042	0.0081
	(0.0051)	(0.0467)	(0.4978)	(0.0060)	(0.0726)	(0.7796)	
Auto parts industry	0.0302	0.0138	−0.0419	0.0349	0.0185	−0.0347	0.0362
	(0.0423)	(0.0219)	(0.1003)	(0.0421)	(0.0236)	(0.1003)	
Papermaking industry	−0.0822	−0.1205	0.8042	−0.0798	−0.1294	0.5891	0.0369
	(0.0137)	(0.0839)	(0.4614)	(0.0131)	(0.0719)	(0.4001)	

Accordingly, in the technology- and knowledge-intensive industries, such as the basic machinery industry, auto parts industry, and software development industry, the knowledge capital investment has reached a certain scale and has been fully exploited. Therefore, the continuous use of knowledge capital can cause a decline in marginal output. When more technological information is added, the share of knowledge capital in the change in technological innovation efficiency of the above three industries decreases from 0.2843, −0.0347, and 0.0140 to 0.2830, −0.0419, and 0.0139, respectively.

In Table 5, the changes in the regression variance of technological innovation efficiency are compared and studied when technological information is incorporated and not incorporated into endogenous explanatory variables, to analyze the differentiated change in technological innovation efficiency brought by technological information. In the empirical analysis, the variance test method is adopted. According to the variance test results after the regression with two different methods, the hypothesis that there is no differentiation in the change in variance of the clothing industry and software development industry is rejected at the 1% significance level. There is a significant difference in the change in variance of the two industries because of the different degree of influence from technological information. The hypothesis that there is no differentiation in the change in variance of the other six industries is rejected at the 5% significance level. Owing to the influence of technological information, there is an obvious difference in the change in technological innovation efficiency. By penetrating the elements of other forms, technological information

indirectly affects the input–output ratio of various innovation-related elements and has a significant effect on the allocation efficiency of these elements, thus producing differentiated technological innovation efficiency. The source, formation, structure, and change in variance have different results.

5.5. Continuous Utilization of Technological Information and Analysis of the Elasticity of Substitution among Innovation-Related Elements

In the empirical research, the quantile regression method is adopted. First, this paper analyzes the changes in technological information and explores the elasticity of the substitution of material elements and human capital with each unit of knowledge capital and the change in the efficiency of technological innovation, resulting in the elasticity of technological innovation output. The three quantiles were 0.25, 0.5, and 0.75. According to the regression results, the continuous change in technological information has a real-time impact on the output of technological innovation. Technological information is affected by a large number of unobservable variables, and as a result, there are continuous changes in technological information at each quantile. Owing to the significantly differentiated influence caused by different variables, the output level of technological innovation greatly fluctuates. For example, with the change of one unit in technological information, the output level of the clothing industry has continuously increased from −0.3413 to −0.3163 and then to −0.2003. The output level of the basic machinery industry, auto parts industry, software development industry, communication transmission industry, and medical instrument industry showed a V-shape trend, which decreased from 0.2911, −0.0813, 0.1716, −0.2797, and −0.2732 to 0.2778, −0.3496, −0.1194, −0.7916, and −0.3346 and then increased to 0.4969, −0.2826, −0.0327, −0.5057, and −0.3269, respectively. In the computer equipment industry and papermaking industry, the contribution of the continuous mining of technological information to the output level of manufacturers increased from −0.0461 and −0.0384 to 0.0454 and −0.2519 and then decreased to −0.4919 and −0.9474, respectively. In general, the in-depth mining and the utilization of incomplete technological information are required. With the increasingly refined allocation of innovation-related elements, it is more necessary to transform incomplete technological information into relatively complete technological information and complete technological information. Incomplete technological information that cannot be transformed has a more obvious impact on the improvement of the output level, resulting in great fluctuations in the output level. There are significant differences in the change in output between industries. This is because incomplete technological information cannot be fully identified and transformed in the process of continuous utilization, and it will cause greater fluctuations in output during the allocation of innovation-related elements, thereby significantly improving the input–output ratio of innovation-related elements.

When the knowledge capital investment replaces the material element investment, the effect of this substitution elasticity on the output of innovation-related elements is relatively stable. According to the results in Columns (4)–(6) of Table 6, in terms of the clothing industry and the medical instrument industry, the substitution of material elements with knowledge capital has a continuous effect on the output level. At the three quantiles, the effect increases from −0.000139 and −0.0101 to 0.0001428 and 0.0109 and then decreases to 0.000076 and −0.0062. With respect to the continuous effect on the output level thanks to the elasticity of substitution of material elements with knowledge capital in the papermaking industry and software development industry, at the three quantiles, the effect changes from −0.0115 and 0.0091 to −0.0196 and 0.0089 and then to −0.0168 and 0.0115. Regarding the continuous effect of this substitution elasticity on output in the basic machinery industry, computer equipment industry, and communication transmission industry, at the three quantiles, the effect decreases from 0.0043, 0.0085, and 0.0306 to 0.0031, 0.0053, and 0.0238 and then to 0.0015, 0.0009, and 0.0167, respectively. Compared with the continuous influence of technological information on innovation output, the elasticity of the substitution of material element investment with knowledge capital brings a rel-

atively balanced change to innovation output because the substitution can help identify and absorb a large amount of incomplete technological information, contributing to the optimized and reasonable allocation of the two innovation-related elements, with little redundancy and waste. The elasticity of the above substitution also shows that when the innovation-related elements in the form of knowledge and information penetrate material elements, a large amount of technological information is generated and automatically transformed and utilized, and the elements in different forms are more integrated. Hence, there is great potential for the optimization of technological innovation efficiency. When a large amount of technological information contained in innovation-related elements in the form of knowledge and information meets the need for material element allocation, the output efficiency of innovation-related element investment reaches the optimal state. The elasticity of continuous substitution between the two invested elements enables the innovation output level to generally remain a stable change, without great fluctuations. Given that the information on material elements needs to be further discovered and utilized, there is also potential for further optimization.

Table 6. Analysis of substitution elasticity of the continuous utilization of technological information and innovation elements.

Industry	Tin Output Elasticity			VFA/VIA			VPS/VIA			Means
	Q1	Q2	Q3	Q1	Q2	Q3	Q1	Q2	Q3	
Computer equipment industry	−0.0461 (0.2166)	0.0454 (0.3024)	−0.4919 (0.4180)	0.0085 (0.0115)	0.0053 (0.0097)	0.0009 (0.0380)	0.0207 (0.0632)	0.0141 (0.0685)	0.0392 (0.1243)	0.4777
Software development industry	0.1716 (0.0924)	−0.1194 (0.1816)	−0.0327 (0.2177)	0.0091 (0.0088)	0.0089 (0.0084)	0.0115 (0.0113)	−0.0002 (0.0138)	−0.001 (0.0089)	−0.0024 (0.0175)	0.3906
Communication transmission industry	−0.2797 (0.1779)	−0.7916 (0.3461)	−0.5057 (0.6192)	0.0306 (0.0298)	0.0238 (0.0320)	0.0167 (0.0571)	0.0152 (0.0352)	0.0118 (0.0779)	0.0082 (0.0981)	0.4715
Medical instrument industry	−0.2732 (0.1379)	−0.3346 (0.2013)	−0.3269 (0.3191)	−0.0101 (0.0366)	0.0109 (0.0741)	−0.0062 (0.0766)	−0.0068 (0.0485)	−0.0291 (0.0853)	0.0581 (0.0581)	0.4953
Basic machinery industry	0.2911 (0.1521)	0.2778 (0.3445)	0.4969 (0.4282)	0.0043 (0.0163)	0.0031 (0.0394)	0.0015 (0.0625)	0.0661 (0.0659)	0.1102 (0.0594)	0.1365 (0.1233)	0.4691
Clothing industry	−0.3413 (0.2087)	−0.3163 (0.3419)	−0.2003 (0.4048)	−0.00014 (0.00021)	0.000143 (0.00027)	0.000076 (0.000428)	0.0726 (0.0289)	0.0581 (0.0384)	0.0317 (0.1464)	0.3585
Auto parts industry	−0.0813 (0.1646)	−0.3496 (0.1990)	−0.2826 (0.4270)	0.0042 (0.0156)	−0.0077 (0.0267)	0.0081 (0.0241)	0.0103 (0.0304)	0.0009 (0.0378)	−0.0093 (0.0641)	0.4773
Papermaking industry	−0.0384 (0.5587)	−0.2519 (0.4869)	−0.9474 (0.4929)	−0.0115 (0.0046)	−0.0196 (0.0084)	−0.0168 (0.0188)	0.0448 (0.0607)	−0.0168 (0.0803)	−0.1142 (0.2026)	0

According to Columns (7)–(9) in Table 6, the contribution of the elasticity of the substitution of human capital with knowledge capital investment to the innovation output is relatively stable. In the computer equipment industry and medical instrument industry, at three quantiles, the contribution decreases from 0.0207 and −0.0068 to 0.0141 and −0.0291 and then increases to 0.0392 and 0.0581, respectively. In the clothing industry, auto parts industry, software development industry, communication transmission industry, and papermaking industry, the contribution of the elasticity of the substitution of human capital with knowledge capital investment to the innovation output continuously decreases at three quantiles, from 0.0726, 0.0103, −0.0002, 0.0152, and 0.0448 to 0.0581, 0.0009, −0.0011, 0.0118, and −0.0168 and then to 0.0317, −0.0093, −0.0024, 0.0082, and −0.1142, respectively. In the basic machinery industry, the contribution of the elasticity of the substitution of human capital with knowledge capital investment to the innovation output continuously increased at three quantiles, from 0.0661 to 0.1102 and then to 0.1365. The elasticity of substitution between these two elements reflects the share of human capital that can be replaced by

adding one unit of knowledge capital investment, and it can bring continuous and stable change in innovation output, when compared with the share of material element investment replaced by knowledge capital. Because human capital can subjectively identify and absorb technological information in the process of innovation-related element allocation, technological information can to a greater extent be absorbed and applied. Incomplete technological information can be more fully transformed into complete technological information. Human capital has the function of subjective judgment and optimal selection. When knowledge capital replaces human capital, real-time adjustments will be made according to the change in technological information to meet the need of innovation element allocation. There will be no advance spillover of technological information or lagging behind on the innovation element allocation. When knowledge capital replaces human capital, the acquisition of complete technological information can significantly optimize the allocation of innovation-related elements and improve the input–output ratio. In terms of the change in the quantity of the two elements involving substitution, substitution timing and the correlation with output, priority should be given to steadily and continuously improving the output level by investing a given number of innovation-related elements, fully utilizing complete technological information, optimizing the allocation proportion of elements, and ensuring that the structure and the quantity of the invested elements meet the need of input–output optimization.

5.6. Stochastic Change in Technological Innovation Efficiency Caused by Knowledge Capital Investment under the Condition of Gradual Change in Technological Information

Different from material element investment, knowledge capital in the form of technological information has strong permeability and diffusion and can be quickly integrated into the material element investment. The output efficiency of its investment is affected mainly by technological information. Table 7 focuses on the analysis of the incremental change in technological innovation efficiency and its regression results caused by knowledge capital under the conditions of incomplete technological information, relatively complete technological information, and complete technological information. Columns (1) and (5) in Table 7 respectively show the incremental changes in technological innovation efficiency in the eight industries and their elasticity of change with knowledge capital investment. In the clothing industry, basic machinery industry, computer equipment industry, auto parts industry, software development industry, communication transmission industry, medical instrument industry, and papermaking industry, the incremental changes in technological innovation efficiency fluctuate around 1, which are stated as follows: 1.3471, 1.6429, 1.1407, 0.8864, 0.7925, 1.0620, 0.9695, and 2.9275. Additionally, the corresponding elasticity of change with knowledge capital investment is 0.5371, 0.3749, 0.7468, 0.3235, 0.5315, 0.5587, 0.4911, and 294.49. Except for the great change in the papermaking industry, the other industries have remained at a relatively stable level.

According to the results in Columns (2)–(4) of Table 7, under the conditions of incomplete technological information, relatively complete technological information, and complete technological information, the contribution of knowledge capital investment to technological innovation efficiency is analyzed by using the OLS regression method. With the gradual change in technological information, the contribution of knowledge capital in the clothing industry gradually increases from −0.0547 to 0.6832 and then to 1.7307; the contribution of knowledge capital in the basic machinery industry and communication transmission equipment industry first decreases from 0.7566 and −0.2465 to 0.2925 and −0.4351 and then increases to 10.5793 and 13.2010, respectively; the contribution of knowledge capital in the computer equipment industry and medical instrument industry increases from 0.0026 and 0.0863 to 11.0803 and 0.4071 and then decreases to −9.6963 and −1.3527, respectively; the contribution of knowledge capital in the auto parts industry, software development industry, and papermaking industry decreases from 0.0091, −0.0092, and 0.0035 to −0.7865, −4.0773, and −0.0675 and then to −2.4067, −1.3527, and −8.9328, respectively. In different industries, with the gradual change in technological information,

the contribution of knowledge capital investment to the increment of technological innovation efficiency is quite different, and the stochastic change is significant [33]. Columns (6)–(8) in Table 7 reflect the elasticity of change in technological innovation efficiency caused by knowledge capital investment and show the regression results. In the clothing industry, computer equipment industry, auto parts industry, and medical instrument industry, with the gradual change in technological information, the shares of knowledge capital investment in the elasticity of change in technological innovation efficiency increase from −0.0105, −0.2805, −0.0114, and −0.0049 to 0.6078, 1.4605, 0.6617, and 0.6239 and then decrease to −5.3915, −4.1181, −10.0297, and −0.0761, respectively. In the basic machinery industry, the share of knowledge capital investment increases continuously from −0.1231 to 0.0721 and then to 0.5477. In the software development industry, communication transmission equipment industry, and papermaking industry, the shares of knowledge capital investment decrease from −0.0069, −0.1604, and −0.0024 to −0.6611, −1.5307, and −0.0541 and then decrease to −4.0203, −114.61, and −12.3942, respectively. The impact of knowledge capital investment in eight industries on the elasticity of change in technological innovation efficiency is significantly different.

Table 7. Analysis on the effect of technological innovation efficiency differentiation under the gradual change in technological information.

Industry	ΔAR	Reg VIA			εAR	Reg VIA		
		TIn < 0.3	0.3 < TIn < 0.7	TIn > 0.7		TIn < 0.3	0.3 < TIn < 0.7	Tin > 0.7
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Computer equipment industry	1.6429	0.0026 (0.0407)	11.0803 (4.9906)	−9.6963 (0.3450)	0.5371	−0.2805 (1.7853)	1.4605 (0.8443)	4.1181 (0.1416)
Software development industry	0.7925	−0.0092 (0.0125)	−4.0773 (2.5820)	−4.5991 (7.2893)	0.5315	−0.0069 (0.0178)	−0.6611 (0.5369)	−4.0203 (3.9616)
Communication transmission industry	1.0621	−0.2465 (0.3053)	−0.4351 (1.2501)	13.2011 (53.9551)	0.5587	−0.1604 (0.0986)	−1.5307 (2.2867)	−114.61 (103.11)
Medical instrument industry	0.9695	0.0863 (0.1365)	0.4071 (0.7163)	−1.3527 (14.1209)	0.4911	−0.0049 (0.0349)	0.6239 (0.3860)	−0.0761 (5.5895)
Basic machinery industry	1.1407	0.7566 (0.8255)	0.2925 (0.2331)	10.5793 (30.8033)	0.3749	−0.1231 (0.1671)	0.0721 (0.2706)	0.5477 (5.3120)
Clothing industry	1.1407	−0.0547 (0.0992)	0.6832 (0.4977)	1.7307 (4.0152)	0.7468	−0.0105 (0.0137)	0.6078 (1.2818)	−5.3915 (1.9406)
Auto parts industry	0.8864	0.0091 (0.0261)	−0.7865 (1.8862)	−2.4067 ()	0.3235	−0.0114 (0.0967)	0.6617 (0.5961)	−10.0297 ()
Papermaking industry	2.9275	0.0035 (0.0226)	−0.0675 ()	−8.9328 (23.9232)	294.49	−0.0024 (0.0055)	−0.0541 ()	−12.3942 (2.7680)

6. Conclusions and Prospects

This paper focuses on how the endogenous change in technological information plays a role in the investment of knowledge capital, human capital, and material elements and profoundly changes the input–output relationship in the allocation of innovation-related elements. Technological information is affected by additional interference factors. Although technological information is not a physical-form element in the element allocation, it can transform the external influence into endogenous change, which directly leads to the stochastic change in technological innovation efficiency.

This paper introduces the allocation of innovation-related elements into the research on the relationship between the endogenous change in technological information and the stochastic change in technological innovation efficiency, and it analyzes the correla-

tion between knowledge capital, human capital, and material elements. Focusing on the internal relationship between the endogenous change in technological information and the knowledge capital investment, the output of innovation-related elements, and the investment of a small share of knowledge capital, this study analyzes how this relationship leads to the stochastic change in technological innovation efficiency, explores how the endogenous change in technological information causes the variation in substitution coefficient of innovation-related elements, and identifies the deeper reasons for the formation of stochastic change in technological innovation efficiency. In the empirical analysis, the generalized method of moments (GMM), endogenous explanatory variables, and the OLS method are introduced for comparative analysis to discover the source and contribution of the endogenous change in technological information and further solve constraints such as the infeasibility of direct quantification of technological information.

According to the research results, which are different from independent tangible elements, the endogenous change in technological information can reduce friction, decrease costs, improve efficiency, and gradually reduce the deviation between knowledge capital investment and the changing trend of technological innovation efficiency. The driving forces are the repeated use of innovation-related elements, the gradual elimination of stochastic interference factors, and the lower knowledge capital investment to acquire higher innovation output. In terms of a small share of knowledge capital investment where there are fewer sources of technological information and lower demand, the endogenous change in technological information can be more accurately predicted in the allocation of innovation-related elements, effectively reducing the stochastic change in the efficiency of technological innovation caused by incomplete technological information. In different periods of technological progress, a small share of knowledge capital helps keep a relatively stable relationship between human capital, material element investment, and technological innovation efficiency. There is an endogenous change in technological information in the allocation of innovation-related elements. The proportion of replacing other elements with one additional unit of knowledge capital investment continuously increases. The given innovation output can be achieved with less investment, and the efficiency of technological innovation continuously and steadily rises. When there is no endogenous change in technological information, the proportion of replacing other elements with one additional unit of knowledge capital investment is uncertain, and the output level and technological innovation efficiency change stochastically. The endogenous change in technological information will induce a change in the input–output ratio of various innovation-related elements. Under the condition of given human capital and material element investment, there is a great difference in the duration of endogenous change in technological information between the simultaneous selection and the sequential selection of knowledge capital investment. When one-time instantaneous information or continuous complete information is obtained, separately, the stochastic change in technological innovation efficiency is obvious.

By comparing and analyzing the changes in technological information in the allocation of innovation-related elements, this paper discusses the influence of technological information on the formation of stochastic change in technological innovation efficiency, which is creative to a certain extent. However, the trend of endogenous change in technological information cannot quantitatively be directly analyzed. In the future, extended research should focus on the continuous utilization of technological achievements, the deepening of step-by-step technological progress, and the precise allocation of innovation-related elements.

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