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Industrial Structure Restructuring, Production Factor Allocation Analysis: Based on a Mineral Resource-Intensive City—Jiaozuo City

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Abstract: The importance of sustainable development of the mineral resources industry is self-evident for the reason of that China's primary energy consumption structure has not changed. While the development level is not only affected by resource endowment, but also by technology. At this important historical stage—namely, transforming China's economic growth mode—how to effectively conduct the supply-side reform has a remarkable strategic significance to the national sustainable economic development goal. In general, if we want to seek a sustainable development path for a mineral resource-intensive region, we must answer the binary contradictory relationship between the mineral resources industry. In order to accomplish these targets, we constructed five index layers and selected 14 specific indicators according to the production function followed by using Kolmogorov entropy. Then, we calculated the Pierce coefficient of different industries and the transfer entropy of production factors of some representative industry in different categories. In this way, the structural similarities or differences in the distribution of production factors are empirically examined. The results of our study showed that the industrial layout of the target case—Jiaozuo City—has not been qualitatively changed, most of its industries is still dominated by resources and labor-based enterprises; at the same time, in terms of production factors structure, resource-based industries are not similar to others showing that similarities and differentiation coexisted; the results of transfer entropy revealed that the reason why differences in similarity mainly are R&D expenditures, total investment in fixed assets, and coal consumption.

Keywords: industrial development; entropy; resource-intensive city

1. Introduction

The continuous improvement of global division of labor allows us to understand the truth—only by embedding ourselves in the global division and market system can we achieve sustainable development. This means a more complex supply chain system and collaboration mechanism. The ore beneath the earth is undoubtedly treasure, especially in an era when the level of industrialization has reached its peak. Because only the real possession of mineral resources and rational use, via the continuous adjustment of industrial structure, will the pace of industrial upgrading will not become a source of no water or no roots. However, under this wave of economic globalization and sustainable development [1], how we own and use these treasures is a serious issue. The imbalance between industrial development and economic level has led most of the world's mineral ores to become the focus of capital plunder. Unbalanced trade has seriously damaged the economic interests of the mineral mining and processing countries. Mineral resources can not only become wealth, but may also become a curse of development.

The 2030 Agenda for Sustainable Development highlights issues such as protecting the planet [2], harnessing ecological degradation, more effectively protecting and managing natural resources, and actively addressing global climate change, demonstrating that environmental and ecological sustainability is a core issue in sustainable social and economic development. Therefore, we must adhere to the idea of combining development and ecological protection to prepare a sustainable future for our country and the world as global climate issues continue to intensify.

From a national level, many countries are now doing their utmost to explore a sustainable development model that suits their needs. This model must be able to meet a long-term equilibrium between economic growth and the environment and human society. For example, the United States and the European Union have formulated policies and regulations for energy conservation and emission reduction [3–5]. Asia with development potential and economic vitality is under tremendous pressure from environmental remediation and energy conservation and emission reduction due to extensive rapid industrialization. The carbon emissions trading market and improved production technologies are moving towards sustainable development [6,7]. From this, it can be seen that the world is trying to achieve sustainable development through industrial restructuring.

As for China, the report of the 19th CPC (Communist Party of China) National Congress pointed toward "building a modern economic system" which confirms that China's economy is in the period from high-speed growth to high-quality development. This period is undoubtedly crucial for the transformation of development modes, the optimization of economic structure, and growth momentum. How to complete this economic transformation, promote the free flow of production factors, and transform its partial disorderly development is undoubtedly a key.

In the past 20 years of rapid economic growth, it is undeniable that resource misallocation caused a waste of resources which remains concealed to some extent. TFP (Total factor productivity) is widely regarded as one of the key indexes to measure the efficiency of industrial structure and economic growth quality [8–10]. Xu Yanxiang [11] used the dual method to calculate Chinese TFP of the last 30 years, and found that the contribution rate is only 2.5%. By using stochastic frontier analysis, Yu Yongze [12] found the rate is only 4.5%, showing that the efficiency of China's production factor allocation has not been significantly improved. The extensive resource exploitation and the corresponding consequences caused by resource misallocation are particularly prominent in resource-intensive cities. We can see a glimpse from the "National Resource-based City Sustainable Development Plan (2013–2020)" issued by the State Council of China in 2013 stating that so far, China has 262 resource-intensive cities at or above the county level, of which 69 are resource-exhausted cities. These cities have laid the foundation for China's industrialization, while they have also shown a trend of "tidal rise and fall", namely once resources begin to dry up or extraction costs are too high, they face the dilemma of ensuring sustained economic growth.

The resource curse theory, put forward by Auty [13], has a strong explanatory power to most of the mineral resource-intensive regions, this theory says that mineral resource-intensive regions are unable to achieve a smooth transition from mineral resources industry to alternative industry. Although the Chinese government has given huge financial support—as an initial government support—in order to revive the glory of these cities, however, because of the main economic growth point of resource-based cities is non-renewable natural resources, this creates a singlular local labor structure with a strong crowding out effect on other industries. Additionally, coupled with the destruction of ecological environment and under the economic background of "new normal", "people, environment and industry" seem to present a "ternary paradox" relationship [14]. On the other hand, since 2015, China has vigorously promoted supply-side reform. The year-on-year ratio of industrial companies' profits to energy and commodity prices is highly synchronized, which means that the price factor has become significant. In this constant volatility of the energy market, there is often a reciprocating economic behavior in resource-based cities. That is, when resource prices or downstream industries that rely on resource development are in a downturn, local governments may try to introduce other industries to change industry and manpower structure, but when the market rebounds, capital and manpower would flood into resource-based industries [15–17]. However, in the long run, China's "supply-side structural reform" relies on the output of superior production capacity and the application of new technology, and in terms of the external economic environment, in today's continuous globalization, the structural differences between industries and the imbalance of linkages has led to the level of development differences in regions normally becoming poles apart. Meanwhile the success of industrial upgrading has a profound impact on the security of regional economic systems. These issues pose a challenge to the mineral resources industry and puts the traditional path, namely dependence on resource endowment, into a desperate situation.

2. Literature Review

For a specific region, the relationship between industries is related to many aspects, for example, energy efficiency, productivity, economic development benefits, social, and public services [18–20]. In order to study these issues, many scholars adopted some more convenient way that is based on the traditional industry classification method, and the corresponding datasets are mostly derived from the national or provincial level. From this paradigm, the industrial structure transformation path research has yielded more results [21–23]. The classical "Clark's Law" reveals the delicate relationship between labor and industrial structure [24,25], namely labor force will evolve spontaneously with the change of three industries. China's economic development basically follows the pattern of gradual advancement, that is, it hopes that the economic development of some regions can gradually spread to other regions. However, this 'convergence' vision has not yet been realized, on the contrary, the economic gap between regions is constantly expanding. According to the classical school, due to the improvement of market mechanism and the sensitivity of price fluctuation, industry will tend to be balanced from a partial equilibrium to a global equilibrium. However, as the degree of economic globalization deepens, more and more scholars are concerned about that the flow of factors among the third industry has intensified, the complexity of interaction between industrial organizations is unprecedented [26,27]. Additionally, the blind area of market mechanisms leads to imperfection, which distorts price information via multiple transaction processes. Therefore, the industry's self-equilibrium is almost impossible, and the ambiguous relationship of two entities introduces some difficulties for us to analyze the change of industrial structure [21,28–30]. In addition, because of the asymmetry of information, there will be different principal–agent relationships between the various entities in the industrial chain. Meanwhile, every participant can change their roles according to different scenarios so as to maximize production efficiency [31–35]. This means that without a consideration of the industrial output efficiency of specific regions, scientific and technological research, and economic behaviors in the industrial chain, the analysis method in the framework of three industries is biased to some extent. The existing research mainly applies macroscopic data analysis to judge industrial development tendencies, but for microcosmic enterprise behavior there still needs to be further enrichment. The research of behavior and information exchange between the main entities needs to be deepened urgently.

It is undeniable that the classic Douglas production function constructs a relationship between production factors and output in a minimalist way and describes basic elements needed for a normal operation of economic system. This function simplifies the initial conditions and greatly reduces the number of factors which can describe the relationship of input and output. Apart from that, it constructs a long-term, stable model for economic growth, while basically encompassing the main types of explanatory variables, therefore it is an understanding of the state of economic system toward equilibrium, which provides a basis for us to analyze the changes in the industrial output value. However, from a micro view aiming at some specific industries, Douglas production function does not give a detailed answer. Due to industrial characteristics, different industries will inevitably have different relative requirements of production factors for organizational production. In other words, the allocation of production factors directly determines the industrial development trajectory and potential. For example, high-tech industry invests heavily in research and development, while low-tech manufacturing industry requires a large amount of cheap labor to achieve scale effects. Furthermore, these differences lead to another proposition that deserves attention, that is, even if it is the same element, but due to belonging to different industries, the quality and quantity of elements may be far apart. Therefore, only by deeply analyzing the internal and external environment of industrial development and clarifying the strategy of industrial development, can we allocate production factors to achieve optimal state in a targeted manner. Investigating the similarity of production factor allocation is of great practical significance for summarizing industrial development experience, guiding regional optimization of input, and gradually reducing resource waste. At the same time, it has a macro-level qualitative effect on an in-depth study of the flow between factors. Therefore, the similarity of industrial structure is often used by scholars to compare the structure between regions or industries themselves to derive some general conclusions, thus providing some inspiration for promoting sustainable development of other regions [36,37].

Based on the above study, more researchers focus on flow, price, and market factors. Zhang Youwen [38] pointed out that capital, management, and technology are the elements of high liquidity, while resource endowments are completely illiquid. Some scholars [39–41] discussed that the international flow of production factors leads to allocation in the recipient countries. Li Ying [42] proved that regional heterogeneity is a barrier to the flow of production factors. Kumakura demonstrated that the negative distortion of factor prices promoted the growth of China's export trade. By calculating the macroscopic data of China's import and export, Yang M. et al. [43] verified that the distortion of factor markets can make China's export trade obtain comparative advantage in a period of time, which also proved that under the condition of limited resources reserve, it is necessary to improve the allocation of production factors to promote or maintain economic growth. At the same time, many scholars also pay attention to different economic entities ranging in scale from micro to macro, all of them have their own attributes, this heterogeneity can also lead to imbalance in the allocation of production factors [44–47]. In summary, scholars, at home and abroad, regard the configuration of production factors as a whole 'black box'. The main method of analysis is to obtain the corresponding value by measuring the input and output of that 'black box' and a variable (such as trade, enterprise management, etc.) but this does not further explain the system internal factors of interaction and the mechanism. At the same time, they have not classified and pertinently explored an industry system so as to ensure that to what extent the responding conclusions are non-universal. For a mineral-intensive city, our concern in this paper, the existing main path to realize industrial transformation to achieve sustainable development focuses on the introduction of innovation factors, which is essentially based on the role of technological innovation in the permutation and combination of production factors. On the one hand, new technology replaces the old technology, and thus production efficiency changes accordingly and the existing labor force inevitably needs to be retrained to adapt to these changes. On the other hand, the entry of new technology also changes the inherent structure of industry through altering some partial production factors allocation. However, in the process of mineral resource-intensive areas, economic fluctuations are not stable, and the trajectories between various elements are difficult to describe. Taking into account these uncertain characteristics, first of all, the equations or the constituent elements used in the subsequent steps, must be established on the basis of an explicitly cognition of linear or nonlinear. In particular, considering the complexity of the process of reconfiguring elements in the course of transition from a single industrial structure to a more complex and open new one, we think it is more suitable to select nonlinear theory as the main analysis method in this study [15,48–50].

The correlation between production factors—more precisely, their causality—is important for us to determine the efficiency of allocation so as to rationally allocate resources. Causality is based on statistical assumptions and is mainly used to analyze the intensity of a time series for another time series, especially when we want to have a prediction. However, as mentioned above, the existing studies often start from linear thinking, and their prediction results tend to face more uncertainty due to the fluctuation of reality. Therefore, Granger believes that the introduction of stochastic processes in traditional causality tests can effectively compensate for the shortcomings of traditional methods [51]. On the other hand, considering that when decision makers analyze the value of decision information, there are many factors that influence the final decision. The two most important aspects are the economic cost, which involves the base of benefits, and another one is the credibility of information, these two items together determine the maximum benefits of different programs. The above-mentioned ubiquitous reality shows that the nonlinear situation between elements has a more complicated expansion [52]. Schreiber [53] proposed transfer entropy and pointed out that transfer entropy is not used as an indicator of causality, but is used to quantify the statistical consistency between time series; it essentially describes the causal relationship caused by the flow of information. The more significant impact is that it can better describe the information transfer between time series and uncertainty. In recent years, information-related knowledge has been applied to data processing technologies. G. Ver Steeg [54] introduced transfer entropy to study the causal inference of social networks. By calculating the transfer entropy between different users derived, he deduced the causal relationship indicated the key nodes among users. Li Jingxin [55] constructed a reasonable evaluation system of urban ecosystem service based on entropy theory to explain the potential relationship between health degree and population growth model. Liu Kangsheng [56] applied the concept of transferring entropy to fish swarm algorithms, thus optimizing the rules of fish school behavior and the algorithm. In fact, the advantage of transfer entropy lies in the calculation of the overall system without any causality, and the relationship is constructed by the results, so that the presupposition is subjective and the intrinsic reason of the complex network is revealed. From the perspective of the similarity of industrial factors collocation, this paper explores the relationship between the production factors of different industries in depth and seeks some rules from the results.

This article mainly examines the development of a mineral resource-intensive city, by reconstructing the industrial categories, examining the relationships between the basic production factors of typical industries. Through the comparison results, we can seek a certain degree of similarity to explain why it is difficult for a resource-exhausted city to accomplish an economic transformation. The main contributions of this paper are as follows: First, the primary classification of industries will be carried out by constructing an index system of industrial structure, then we calculate the information entropy and Kolmogorov entropy to evaluate the degree of information dissipation in each industry; Second, we conduct a correlation analysis on some representative industry which belongs to different categories; Third, we analyze the function relationship and the related mechanism of production factors, and try to explore the operation rule of the 'black box' of our target city.

3. Methodology

In 1948, Shannon proposed using the entropy of information sources to define the amount of information. As a dissipative economic system, due to the existence of information costs and information ambiguity, each system participant has its own entropy change, they form an ordered dissipative structure by the mechanism of non-linear interaction [57]. However, their movement has some certain randomness, so it is impossible to satisfy the rational hypothesis, which means that it is the microscopic fluctuation that drives a system away from equilibrium. Entropy, as a measurement of disorder, moves an the abstract understanding of the system state to a specific expression. From the perspective of mathematics, the definition of entropy requires that the attractor to be segmented, furthermore, for considering the infinite subdivision of this segmentation, the amount of information in this dynamic process should be estimated.

Considering the complexity of economic system, especially for an economic system that is undergoing transformation, the network of its internal industry and corresponding production factors is always in a variable nonlinear dynamic environment. Therefore, information entropy alone does not accurately describe the complexity of network changes. Another research branch of nonlinear systems is the reconstruction space. Relevant research shows that one of the important features of nonlinearity is the fractal dimension. Therefore, Kolmogorov entropy [58] can be introduced to effectively describe the dynamic structure of nonlinear system. Based on Kolmogorov entropy, we can analyze the system dimension of each industry and the information dissipation in economic activities, so as to find the commonality between them to reclassify them.

According to the definition of information dimension, we suppose that the probability p_i of the i b is introduced, since the our interest is in how to distinguish between different orbits, we refer to the joint probability $p(i_1, i_2, \cdots, i_m)$ which indicates the probability that the orbital is in the first box, and the probability of the moment $t + \Delta t$ in the second box ..., moment $t + (m-1)\Delta t$ the probability of being in the m box.

$$K = -\lim_{\Delta t \to 0} \lim_{\varepsilon \to 0} \lim_{m \to \infty} \sum_{i_1, i_2, \cdots, i_m} p(i_1, i_2, \cdots, i_m) \cdot \log p(i_1, i_2, \cdots, i_m) \tag{1}$$

where ε is the size of the box. For the motion trajectory with certain regularity, the $K = 0$,while for the random motion, the $K = \infty$ and the chaotic motion K is positive.

3.1. Phase Space Reconstruction

If we want to get Kolmogorov entropy, we have to reconstruct the phase space, which involves solving the problem of two parameters. On the other hand, based on dynamics theory, a disordered time series contain more important information, only when project it into 3D, 4D, or even higher dimensions of space can we observe. Therefore, no matter from the point of Kolmogorov entropy solution or from the theory, we are required to solve the problem of two parameters, that is the delay time(τ) and the dimension(m) in the process of phase space reconstruction.

There are two main methods: derivative reconstruction method and coordinate delay reconstruction method. From the view of mathematics, both of which are feasible for phase space reconstruction. However, from the view of operation, because the differential is more rigorous to data requirements, the error is relatively more sensitive, so now the main mainstream is the latter. The original intention of reconstructing the phase space is to try to find the chaotic attractor in the projected high-dimensional space. As a key feature of chaotic system, the chaotic attractor is the stable operation orbit because it is constituted by the important information of other components. The disordered phenomena and chaotic phenomena in the time domain are caused by the stretching, compressing, translating and rotating of chaotic attractor orbits in varied time and space. On the basis of Packard, through a large number of mathematical proofs, Takens in 1981 [59] gave the relationship between the embedding dimension—m, and the original dimension—d:

$$\mathrm{m} \geq 2\mathrm{d} + 1 \tag{2}$$

which indicating that when the phase space is reconstructed, if the equation is satisfied, then, in the constructed R^m space, the chaotic attractor can be recovered better meanwhile the two dynamic systems remain differentially homologous.

There are generally two kinds of method for τ, m, one of it regards that they can be independently estimated without dependency relationship, the methods for delay time *tau* are: *mutual information method, autocorrelation method, mean displacement method, complex autocorrelation method*; as for m they are: *geometric invariance, false nearest neighbors (FNN),* and *FNN-Cao*. Another view holds an opposite opinion, namely τ, m need to be determined at the same time and cannot be brutally fragmented.

We compare the application and advantages and disadvantages of each method. Additionally, taking into account the object in our study is a region's industry system, the collection of economic data is difficult while most of them are basically collected in years; therefore, the requirement of dataset quantity of some methods cannot basically achieve. After comprehensive consideration, we adopt autocorrelation method to get the delay time τ and FNN-Cao to obtain the embedding dimension m.

3.1.1. Self-Correlation Method

The delay time(τ) determines the correlation between components after reconstructing phase space, therefore, the appropriate τ is significant. If τ is too small, each component contains mostly the same information, thus losing the significance of reconstruction; if it is too large, components are independent, then the trajectory of chaotic attractors cannot generalize the rule of the system.

The autocorrelation method [60,61] is a widely and a very mature method for solving τ, which is based on the study of the correlation of time series. For continuous variable $x(t)$, the autocorrelation function $C(\tau)$ is defined as

$$C(\tau) = \lim_{T\to\infty} \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} x(t)x(t+\tau)dt. \tag{3}$$

As a rule of thumb, the iteration loop does not end until the value of Equation (3) drops to $(1 - 1/e)$ of the initial value, the corresponding τ is the delay time.

The definition of autocorrelation function explains the extent of correlation between the obtained value and the initial value, the smaller the τ is, the greater the $C(\tau)$ is, then the closer the $x(t),\ x(t+\tau)$ is. Furthermore, $C(\tau)$ is a standard even function that can also be used to investigate the evenness and the oddness of reconstructed phase space. Similarly, if $x(t)$ is a periodic function, thus $C(\tau)$ also has periodicity, which can reduce the workload.

Equation (3) is for the continuous variables, for discrete data $x_1,\ x_2,\ \cdots,\ x_n,\ \cdots,$ the autocorrelation function is defined as Equation (4)

$$R_{xx}(j\tau) = \frac{1}{N} \sum_{i=0}^{N-1} x_i x_{j\tau+i}. \tag{4}$$

3.1.2. FNN-Cao Method

The Cao [62] is much more optimized than FNN, although its foundation is FNN. Its advantages are: (1) the requirement of the number of parameters is low, namely only need τ; (2) the random signal and the deterministic signal are distinguished with high efficiency; (3) the length of $\{x_i\}$ is not required in large scale, in other words, a sequence with small data amount can also be adopted.

By defining in a d-dimensional phase space, each vector, $X(i) = \{x(i),\ x(i+\tau),\ \cdots,\ x(i+(d-1)\tau)\}$, has a nearest point $(X^{NN}(i))$ within a distance

$$R_{d+1}^2 = R_d^2(i) + \|x(i+\tau d) - x^{NN}(i+\tau d)\|. \tag{5}$$

If $R_{d+1}(i)$ is much larger than $R_d(i)$, it can be considered that the two points that are not adjacent in the high-dimensional chaotic attractor become two adjacent points when projected onto a low-dimensional orbit. Therefore, the criterion in the Cao method is as showed in Equation (6).

$$\begin{gathered} E^*(m) = \frac{1}{N-m\tau} \sum_{i=1}^{N-m\tau} \left| x(i+m\tau) - x^{NN}(i+m\tau) \right| \\ E2(m) = \frac{E^*(m+1)}{E^*(m)} \end{gathered} \tag{6}$$

For a random sequence, the $E2(m)$ will always be 1 for there is no correlation between variables; for a deterministic sequence, the correlation is dependent on m, so when $E2(m)$ is not equal to 1, the corresponding m is what we want.

3.2. Transfer Entropy

The main theme of this paper is the interaction among production factors. Although we can roughly infer some similarities and differences between industries by combining the classical production function with the real situation, we still need to do some data analysis on the resource-intensive city. So, first, we must address is how to accurately measure the similarity of industrial production factors in a case area in order to make a certain evaluation on the allocation of industrial production factors at the basic level. Therefore, starting from this idea, this paper selects the Pearson correlation coefficient recognized in academic circles as the similarity index of industrial production factors. On the basis of Pearson correlation coefficient, we can identify the convergence of production factors input to some extent. After this basic judgment, it is necessary to further study the driving mechanism, it is the function of production factors of different industries that essentially means that some factors in some industries have a siphon effect on other production factors, while on the contrary having a crowding out effect on the remaining factors. Then how to test the interaction between factors and whether this interaction has asymmetry is significant in this paper.

With the advent of the era of big data, the application of data has become more extensive. In particular, the information carried by data and the related theories and calculation methods are all based on the characteristics of probability distribution that have attracted the attention of many scholars and have made the research branch be more and more popular. Transfer entropy is based on the information theory of Shannon and Kolmogorov et al., and it is Schreiber [53] who is the first person employed it as an important method to measure the amount of information transmission of two time series, he also proved that transfer entropy has the equivalence of Granger causality test. The advantage lies in revealing the asymmetry of the information transmission in two time series, and it is more sensitive and accurate to measure the nonlinear time series. In addition, the main purpose of causality is to observe whether some changes in interpretation time series have an effect on the prediction of interpreted time series, while the transfer entropy is more focused on examining whether interpretation time series contributes to the state transition of interpreted time series, suggesting that it has uncertain nonlinear features [63].

Let X and Y represents time series respectively, and $T_{x \to y}$ denotes the transfer entropy of X to Y. The formula is

$$T_{y \to x} = H(X_t|X_{t-1}) - H(X_t|X_{t-1}, Y_{t-1}). \tag{7}$$

$H(X_t|X_{t-1})$ represents the uncertainty of X at t time only when X is observed at $t-1$ time, and so forth, $H(X_t|X_{t-1}, Y_{t-1})$ represents the uncertainty under the condition of increasing the observation of Y at $t-1$ time. A rule must to be followed is that when $T_{y \to x} = 0$, it means that there is no information transfer effect between X and Y, and they are conditional independent relations. When $T_{y \to x} > 0.$, it means that Y has an information transfer effect to X, so we can indirectly predict the future of X by collecting relevant information of Y. Schreiber [53] proposed a specific calculation method in 2000 assumed that X and Y are respectively approximated by a steady-state Markov process. Namely,

$$T_{y \to x} = \sum p(x_{t-1}, x_t^{(k)}, y_t^{(l)}) log \frac{p\left(x_{t+1}\middle|x_t^{(k)}, y_t^{(l)}\right)}{p\left(x_{t+1}\middle|x_t^{(k)}\right)} \tag{8}$$

$p(x_{t-1}, x_t^{(k)}, y_t^{(l)})$ is the probability of simultaneous occurrence of x_{t+1} and $x_t^{(k)}, y_t^{(l)}$; $p(\, x_{t+1} \big| x_t^{(k)}, y_t^{(l)}\,)$ denotes the probability of x_{t+1} . occurrence when given $x_t^{(k)}, y_t^{(l)}$; $p(\, x_{t+1} \big| x_t^{(k)}\,)$ indicates the probability of x_{t+1} appears only when $x_t^{(k)}$ appears; $x_t^{(k)}, y_t^{(l)}$ represents X and Y conform respectively to k and l order Markov processes. Generally, we ordered $k = l$, which can be considered as the length of time series.

3.3. Indicator Data Set Source

Indicator Selection

As an actual carrier of resource elements that can play an economic role, resource-intensive regions can highlight the delicate and complex relationship between production factors in an economic transition period. We select a resource-exhausted city—Jiaozuo City, identified by the State Council of China—as a study case. In the history of 'coal-thriving', Jiaozuo City is located in the northwestern part of Henan Province, after the initial stage of the planned economy and the market economy, it gradually formed an industrial city dominated by energy, metallurgical, and other energy-consuming industries. As an important transportation hub in northwestern Henan and southeastern Shanxi, Jiaozuo City's geographical location advantage is self-evident. Since it is included in one of the three resource-exhausted cities in the central region from 2008, the local government and enterprise have made great efforts to change its industrial structure in the past 10 years. So how effective are these efforts? We need a scientific test. Meanwhile, the dataset source is mainly the China Statistical Yearbook, years 2006–2016, which is enough to show a series of economic changes as a resource-exhausted city.

It is generally believed that production factors affecting industry's final output and development will all play a role in the industrial change. These related influencing factors were initially described by the Douglas production function, which constructs the corresponding relationship from the three perspectives—namely labor, technology, and capital. Among them, in terms of technology investment, because technology has higher requirements for high quality of employees who are the main source of scientific and technological innovation, and innovation processes cannot be supported by funds. Therefore, it is mainly expressed by the R&D personnel and R&D expenses [64]. From the perspective of capital, it is the most simple and direct means of forming industrial clusters. It is also related to the sustainability of industrial restructuring. Therefore, this paper selects Total Investment in Fixed Assets and Total Assets [65]. The input of labor force, because it is the main agent for production and also the main source of production cost of enterprise, is expressed by labor costs and number of employees [66]. It should be noted that the scale effect can bring about an increase in economic benefits, and can contribute to the efficiency of factors allocation. In addition, since most mineral industries require energy as a driving force for production, energy consumption can measure the scale of industry. In summary, we select electricity consumption, coal consumption, number of enterprises, production scale, and sales amount [67,68]. Finally, as for total output, on the one hand, we need to consider the absolute value, and more importantly, we need to consider its input-output efficiency to reflect the organizational production capacity, so we adopt per capita gross product, energy consumption per unit of GDP, electricity consumption per unit of GDP, and total liabilities. Then, all indicators are summarized as shown in the Table 1.

In conclusion, we count all industries above the major scale (which means that from 1998 to 2006, this includes all state-owned and non-state-owned industrial legal entities with revenue of major business of 5 million yuan and above; from 2007 to 2010, this includes all industrial legal entities with annual main business income of 5 million yuan and above; since 2011, this includes an industrial legal entity with annual main business income of 20 million yuan and above) in Jiaozuo City, a total of 3510 data points followed by conducting K-entropy operations. For convenience, 26 industries (which are based on the "National Economy Industry Classification" of China (GB/T4754-2017), which is according with the "International Standard Industrial Classification for all Economic Activities" of UN (ISIC rev.4), and Chinese standard mainly uses the industrial activity units and legal entity units as the industrial units.) and 15 indicators are numbered as follows in Table 2.

Table 1. Industry category and number.

Industry Category and Number	Industry Category and Number
Mining and Washing of Coal (A1)	Manufacture of Medicines (A14)
Mining and Processing of Nonmetal Ores (A2)	Manufacture of Chemical Fibers (A15)
Processing of Food from Agricultural Products (A3)	Manufacture of Rubber and Plastic Products (A16)
Manufacturing of Foods (A4)	Manufacture of Non-metallic Mineral Products (A17)
Manufacture of Liquor, Beverages and Refined Tea (A5)	Smelting and Pressing of Ferrous Metals (A18)
Manufacture of Tobacco (A6)	Smelting and Pressing of Non-ferrous Metals (A19)
Manufacture of Textile (A7)	Manufacture of Metal Products (A20)
Manufacture of Textile, Wearing Apparel and Accessories (A8)	Manufacture of General Purpose Machinery (A21)
Manufacture of Leather, Fur, Feather, and Related Products and Footwear (A9)	Manufacture of Special Purpose Machinery (A22)
Processing of Timber, Manufacture of Wood, Bamboo, Rattan Palm, and Straw Products (A10)	Manufacture of Railway, Ships, Aerospace, and Other Transport Equipment (A23)
Manufacture of Paper and Paper Products (A11)	Manufacture of Electrical Machinery and Apparatus (A24)
Printing and Reproduction of Recording Media (A12)	Manufacture of Measuring Instruments and Machinery (A25)
Manufacture of Raw Chemical Materials and Chemical Products (A13)	Production and Supply of Electric Power and Heat Power (A26)

Table 2. Indicator and number.

Indicator	Indicator
R&D Personnel (B1)	Energy Consumption per Unit of GDP (B9)
R&D expenses (B2)	Electricity Consumption per Unit of GDP (B10)
Total Liabilities (B3)	Number of Enterprises (B11)
Total Investment in Fixed Assets (B4)	Number of Employees (B12)
Electricity Consumption (B5)	Sales Amount (B13)
Coal Consumption (B6)	Total Assets (B14)
Labor Costs (B7)	Production Scale (B15)
Per Capita Gross Product (B8)	

In order to eliminate the influence of dimension, all the data should be normalized firstly. According to the following formula

$$u_{ij} = \begin{cases} \frac{(N_{ij} - \eta_{ij})}{(\gamma_{ij} - \eta_{ij})}, & u_{ij} \text{ is the efficiency index} \\ \frac{(\gamma_{ij} - N_{ij})}{(\gamma_{ij} - \eta_{ij})}, & u_{ij} \text{ is the cost index} \end{cases}$$

where u_i is the ordinal parameter of the observed system, u_{ij} is the j index of the ordinal parameter, its value is N_{ij}, and γ_{ij}, η_{ij} is the upper and lower bounds respectively.

Because the result is so big (3510 × 3), in this paper, the first and last three K entropy of each industry are temporarily taken.

4. Results and Analysis

4.1. K Entropy and Industry Classification

From the results in Table 3—which measures the rule of how each evaluation index operates in its own system—we can see that the smaller the K entropy is, the lower the invalidity is. Namely, the development is more benign and the disorderly degree is higher. Be different from information entropy, as it is stated above, K-entropy is on the basis of phase space reconstruction, therefore, the common similarity of each variable can be measured uniformly. The results in Table 3 show that the K-entropy value of various industries in Jiaozuo City is low, indicating that, after a long period of interaction between production factors, the industrial layout has been formed or has been solidified, with the corresponding industrial competitiveness, industrial output value, industrial clusters have their own rules of operation. From this perspective, it is possible to boldly speculate that it is not easy to change the status of resource depletion in Jiaozuo City through the embedding of technology industries; at the same time, technology-related metrics—labor, costs (including internal expenditures, external expenditures), and energy efficiency—are at the bottom, this is means that the chaos is higher and the above conjecture is also supported.

Table 3. Kolmogorov entropy.

A1		*A2*		*A3*		*A4*		*A5*		*A6*		*A7*		*A8*			
B1	*1*	*B8*	*3*	*B1*	*1*	*B1*	*1*	*B1*	*1*	*B3*	*2*	*B1*	*1*	*B3*	*2*		
B2	*2*	*B9*	*11*	*B2*	*2*	*B2*	*2*	*B2*	*2*	*B6*	*4*	*B2*	*2*	*B4*	*1*		
B3	*3*	*B10*	*2*	*B3*	*3*	*B4*	*3*	*B3*	*3*	*B9*	*11*	*B3*	*3*	*B5*	*3*		
B13	*13*	*B11*	*9*	*B12*	*13*	*B10*	*15*	*B13*	*14*	*B10*	*13*	*B13*	*14*	*B13*	*13*		
B14	*15*	*B12*	*1*	*B14*	*14*	*B11*	*14*	*B14*	*13*	*B11*	*12*	*B14*	*13*	*B14*	*12*		
B15	*14*	*B13*	*10*	*B15*	*15*	*B15*	*13*	*B15*	*15*	*B15*	*1*	*B15*	*15*	*B15*	*11*		
A9		***A10***		***A11***		***A12***		***A13***		***A14***		***A15***		***A16***		***A17***	
B3	*2*	*B3*	*1*	*B1*	*2*	*B1*	*1*	*B1*	*1*	*B1*	*1*	*B8*	*3*	*B1*	*1*	*B1*	*1*
B4	*3*	*B4*	*2*	*B2*	*3*	*B2*	*2*	*B2*	*3*	*B2*	*2*	*B9*	*2*	*B2*	*2*	*B2*	*2*
B5	*1*	*B5*	*3*	*B7*	*11*	*B8*	*3*	*B4*	*2*	*B3*	*3*	*B10*	*1*	*B3*	*3*	*B3*	*3*
B11	*15*	*B13*	*11*	*B8*	*12*	*B12*	*13*	*B12*	*14*	*B12*	*13*	*B13*	*11*	*B12*	*13*	*B10*	*14*
B12	*14*	*B14*	*12*	*B11*	*13*	*B14*	*15*	*B14*	*15*	*B14*	*14*	*B14*	*13*	*B14*	*14*	*B12*	*15*
B13	*13*	*B15*	*13*	*B13*	*1*	*B15*	*14*	*B15*	*13*	*B15*	*15*	*B15*	*12*	*B15*	*15*	*B13*	*13*
A18		***A19***		***A20***		***A21***		***A22***		***A23***		***A24***		***A25***		***A26***	
B2	*2*	*B1*	*1*	*B1*	*1*	*B1*	*1*	*B1*	*1*	*B1*	*1*	*B1*	*1*	*B1*	*1*	*B3*	*1*
B3	*1*	*B2*	*2*	*B2*	*2*	*B2*	*3*	*B2*	*2*	*B2*	*3*	*B2*	*2*	*B2*	*2*	*B4*	*2*
B5	*3*	*B3*	*3*	*B3*	*3*	*B4*	*2*	*B3*	*3*	*B3*	*2*	*B3*	*3*	*B4*	*3*	*B5*	*3*
B9	*14*	*B10*	*15*	*B13*	*13*	*B13*	*15*	*B11*	*13*	*B12*	*13*	*B13*	*13*	*B11*	*12*	*B12*	*11*
B11	*13*	*B11*	*14*	*B14*	*15*	*B14*	*14*	*B12*	*15*	*B13*	*14*	*B14*	*14*	*B12*	*11*	*B14*	*12*
B15	*15*	*B15*	*13*	*B15*	*14*	*B15*	*13*	*B15*	*14*	*B15*	*15*	*B15*	*15*	*B14*	*13*	*B15*	*13*

(1) Most of the above-scale heavy industries in Jiaozuo City have low K entropy values in terms of energy consumption and industrial scale, meanwhile, they show similar characteristics of the associated industrial entropy values, thus we can regard it as a correlation between industrial chain cluster and industry factor investment. However, in contrast, the K entropy of the following index of most industries—coal consumption, electricity consumption, investment and labor—is higher, implying that the resource utilization ratio of industries is not high, also the investment is wasted; (2) The K entropy values of Agricultural and Non-Staple Food Processing Industry, Food Manufacturing Industry, Beverage, and Textile Industries is higher, these results mean that the degree of information redundancy is high. Such industries are primary labor-intensive, absorbing a large amount of local labor. However, the labor force differences are not obvious; (3) The Smelting and Pressing of Ferrous Metals Industry, the Smelting and Pressing of Non-ferrous Metals, the Manufacture of General Purpose Machinery Industry and the Manufacture of Special Purpose Machinery Industry have low K entropy values in terms of industry scale, but it is noteworthy that their technical personnel, energy utilization of K entropy is also low, indicating that these industries have certain technical barriers, in other words strong exclusivity.

According to the K entropy results above, this paper reconstructs the industrial classification for Jiaozuo City, as shown in Table 4 below.

Table 4. Industrial structure reconstruction system.

Classification	Industry
Resource Industry	A1, A2
Labor Industry	A3, A4, A5, A7, A8, A9
Low-tech Industry	A6, A10, A11, A17, A18, A19, A20, A26
Medium-tech Industry	A12, A13, A14, A15, A16, A21, A22, A23, A24, A25

4.2. Similarity of Industrial Factor Allocation

Based on the industrial restructuring in Jiaozuo City, we further selected the representative industries in different categories. On the one hand, it not only accords with the rules of industrial classification, but also on the other hand, because the data comes from a specific case, so the characteristics of industry are unique enough to ensure the objective and fairness. The principle of screening sub-sectors is that which can maintain a high level of development in the economic aggregate of each industrial category or have similar trajectories. The reason is mainly as follows: first, it is generally believed that a large economic volume of industry because of its large contribution to the economy, so it must have a certain type of industry representative; second, by studying industries with similar economic track it is helpful to compare the allocation of production factors.

In resource industry, continuous data includes only two categories: Mining and Washing of Coal, and Mining and Processing of Nonmetal Ores, the former has far exceeded the latter in economic gross. Therefore, in the resource industry, we choose the Mining and Washing of Coal. As for labor-intensive and low-tech industry, Manufacture of Leather, Fur, Feather and Related Products; and Footwear and Manufacture of Non-metallic Mineral Products are thriving with maintaining high growth all year round; while in medium-tech industry, Chemical Raw Materials and Chemical Products Manufacturing; Plastic and Rubber Products Industry; and Manufacture of Special Purpose Machinery keep stable growth. A random choice will lack certain persuasive power and may cause the study sample flaw to bring some deviation of results. To sum up, this paper finally selected six industries and renumbered them (B1 = A1, B2 = A9, B3 = A17, B4 = A16, B5 = A13, B6 = A22). The Pearson correlation result is shown in Figure 1.

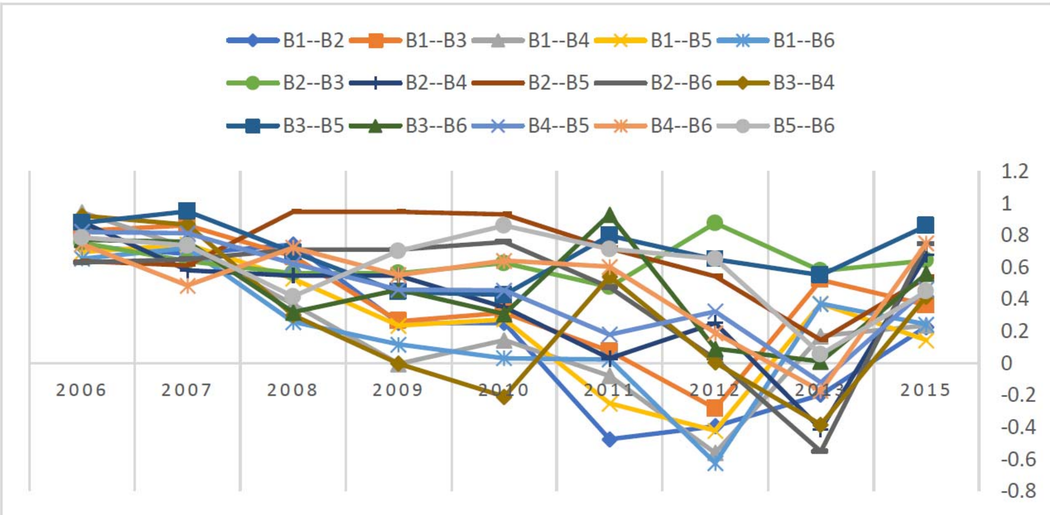

Figure 1. Similarity chart of industry production factor configuration.

From the figure, we can find that the similarity of production factors has a certain degree of volatility. In 2006 and 2007, the similarity of configuration remained basically the same, the fluctuation is most obvious in the period of 2011–2013. Clearly, it is worth noting that their similarity tends to diverge over time which indirectly shows that the production factors are not blindly following the unified standard, but they gradually try to have configuration optimization transition. Further analysis shows that the degree of similarity between B1 and the other five industries has experienced large deviations. It was from the initial similarity above 0.65 to approximately 0.2, it is the reason of that with the development of itself, there may be huge changes in the ratio of production factors in the time interval. We also see that B4, B2, and B5 present a trend of synchronization, although there has been a sharp decline for several years, there is a tendency of climb gradually. This shows that China's technology industry and low-tech industry are gradually adjusting the allocation of production factors.

Similarly, B3 and B4 or B6, B2, and B6 also have the same changes. It is not difficult to find that the similarities and dissimilarities of production factors in the representative industry coexist, which can indirectly reflect the existence of imitations in the process of optimizing production factors allocation. While as for the larger fluctuation, we conjecture that the probable reason may be the vibration effect which is inevitable in the process of industrial structure adjustment.

4.3. Transfer Entropy

Through Figure 1, we examined the trend of similarity of factor configuration in different industries, and also carefully analyzed some related industries with higher similarities. So, how do these similarity changes occur? Is there a specific law for the allocation of production factors? Next, we further examine these issues. We use the transfer entropy to restore the source information of production elements as best as possible.

Based on the results of the dataset, we apply the corresponding colors of red to violet according to the values from small to large to form a transfer entropy color scale table (Tables 5–10). It is necessary to note that the same color may appear differently in a different table because of the difference in the cardinality of different table.

Table 5. Color distribution of mining and washing of coal.

	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	0.0000	0.8444	0.2500	0.1734	0.6726	0.3444	0.4906	0.2500	0.4906
A2	0.7500	0.0000	0.2500	0.3196	0.4226	0.5944	0.2406	0.0000	−0.0094
A3	1.0000	1.0944	0.0000	0.2677	0.6726	0.5944	0.4906	0.2500	0.4906
A4	0.1556	0.3962	0.0000	0.0000	0.0000	0.3444	0.1462	0.0000	0.1462
A5	0.7500	0.5944	0.2500	0.2136	0.0000	0.3444	0.2925	0.0000	0.1462
A6	1.0000	0.8444	0.2500	0.2677	0.4226	0.0000	0.4906	0.2500	0.4906
A7	0.7500	0.5944	0.2500	0.5177	0.6726	0.3444	0.0000	0.0000	0.0944
A8	1.0000	0.8444	0.2500	0.5177	0.6726	0.3444	0.4906	0.0000	0.2406
A9	0.7500	0.5944	0.2500	0.5177	0.5264	0.3444	0.3444	0.0000	0.0000

Table 6. Color distribution of manufacture of leather, fur, feather and related products and footwear.

	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	0.0000	0.6887	0.2976	0.6462	0.5425	0.3444	0.2500	0.3444	0.1579
A2	0.5944	0.0000	0.0995	0.8962	0.5425	0.5944	0.2500	0.3444	−0.0402
A3	0.3444	0.4906	0.0000	0.0000	0.4694	0.3962	0.2500	0.0944	−0.0402
A4	0.5944	0.6887	0.2976	0.0000	0.5425	0.3444	0.0000	0.0000	0.1579
A5	0.3444	0.6887	0.1514	0.3962	0.0000	0.5944	0.2500	0.3444	−0.0402
A6	0.3444	0.6887	0.2976	0.3962	0.5425	0.0000	0.0000	0.3444	0.1579
A7	0.3444	0.4387	0.1726	0.2500	0.5425	0.0000	0.0000	0.3444	0.1579
A8	0.3444	0.6887	0.1726	0.0519	0.5425	0.1462	0.0000	0.0000	0.1579
A9	0.3444	0.4906	0.1726	0.3444	0.5944	0.2500	0.2500	0.3444	0.0000

Table 7. Color distribution of manufacture of raw chemical materials and chemical products.

	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	0.0000	0.2677	0.6981	0.7764	0.3444	0.5944	0.7712	0.2500	0.2500
A2	0.0000	0.0000	0.2500	0.4745	0.0000	0.0000	0.2712	0.0000	0.0000
A3	0.7500	0.5177	0.0000	0.5264	0.0944	0.8444	0.5212	0.2500	0.0000
A4	0.5000	0.0696	0.4481	0.0000	0.0944	0.5944	0.4269	0.2500	0.2500
A5	0.7500	0.5177	0.4481	0.7764	0.0000	0.5944	0.7712	0.5000	0.2500
A6	0.5000	0.3196	0.6981	0.7764	0.3444	0.0000	0.2712	0.5000	0.2500
A7	0.7500	0.2677	0.1981	0.4320	0.3444	0.5944	0.0000	0.2500	0.0000
A8	0.5000	0.2677	0.4481	0.7764	0.3444	0.8444	0.5212	0.0000	0.0000
A9	0.5000	0.2677	0.1981	0.5782	0.3444	0.8444	0.3231	0.0000	0.0000

Table 8. Color distribution of manufacture of rubber and plastic products.

	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	0.0000	0.6981	0.4481	0.2500	0.8444	0.2500	0.2500	0.3444	0.2500
A2	0.2500	0.0000	0.4481	0.2500	0.8444	0.5000	0.0000	0.3444	0.2500
A3	0.0000	0.6981	0.0000	0.2500	0.5944	0.2500	0.2500	0.0944	0.2500
A4	0.2500	0.6981	0.4481	0.0000	0.8444	0.5000	0.2500	0.3444	0.2500
A5	0.2500	0.6981	0.1981	0.2500	0.0000	0.5000	0.2500	0.0944	0.2500
A6	0.0000	0.6981	0.4481	0.2500	0.8444	0.0000	0.2500	0.3444	0.2500
A7	0.2500	0.4481	0.4481	0.2500	0.8444	0.5000	0.0000	0.3444	0.2500
A8	0.2500	0.6981	0.1981	0.2500	0.5944	0.5000	0.2500	0.0000	0.0000
A9	0.2500	0.6981	0.4481	0.2500	0.8444	0.2500	0.2500	0.0944	0.0000

Table 9. Color distribution of manufacture of non-metallic mineral products.

	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	0.0000	0.7852	0.5000	0.5425	0.6981	0.6556	0.6981	−0.0104	0.1038
A2	0.0000	0.0000	0.0000	0.3444	0.2500	0.2500	0.4481	0.0000	0.1038
A3	0.3444	0.4314	0.0000	0.7925	0.6981	0.4056	0.6981	0.0116	0.1038
A4	0.0944	0.4833	0.2500	0.0000	0.4481	0.6556	0.6981	−0.0196	−0.1462
A5	0.3444	0.4833	0.2500	0.5425	0.0000	0.6556	0.6981	0.0000	−0.1462
A6	0.0944	0.5258	0.2500	0.7925	0.9481	0.0000	0.6981	0.0000	0.1038
A7	0.3444	0.6814	0.5000	0.7925	0.9481	0.6556	0.0000	−0.0063	0.1038
A8	0.3444	0.6814	0.2500	0.7925	0.9481	0.1556	0.6981	0.0000	0.1038
A9	0.0944	0.7333	0.2500	0.5425	0.6981	0.2075	0.6981	0.0000	0.0000

Table 10. Color distribution of manufacture of special purpose machinery.

	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	0.0000	0.8231	0.7925	0.5212	0.8444	0.3444	0.4481	0.2925	0.2012
A2	0.0944	0.0000	0.5425	0.7712	0.5944	0.1887	0.6462	0.2925	0.1493
A3	0.5944	0.5731	0.0000	0.7712	0.5944	0.6887	0.8962	0.5425	0.2012
A4	0.5944	1.0731	0.7925	0.0000	0.8444	0.6887	0.8962	0.5425	0.4512
A5	0.5944	0.8231	0.5425	0.7712	0.0000	0.6887	0.8962	0.2925	0.1068
A6	0.2500	0.8231	0.5425	0.5212	0.8444	0.0000	0.4481	0.5425	0.4512
A7	0.1462	1.0731	0.7925	0.7712	0.8444	0.2406	0.0000	0.5425	0.4512

Through the color distribution, we can roughly see that the B1 has the deepest color in the front and the middle; B2 and B3 both concentrate in the middle; B4 has a dark, light-colored jump distribution, while the overall color gradient is warm; B5 and B6 have uniform distribution, but the dark color system is larger than the warm.

The following is a detailed analysis of each specific industry. For the Coal Mining Industry, it can be seen that the input of R&D is relatively large; except for the population of R&D personnel, total investment of fixed assets, and number of enterprises that have information transmission to sales amount, other factors are all zero. In contrast, apart from industrial electricity consumption, other factors are passed on investment in fixed assets; the greatest impact on industrial electricity consumption and coal consumption is mainly the employees and sales amount, and also the R&D personnel and fixed asset investment also has a greater impact on the industry's coal consumption. The biggest effect on the number of enterprises is R&D expense and fixed assets investment. For Manufacture of Leather, Fur, Feather and Related Products and Footwear, R&D is the largest inflow, the second is the consumption of raw coal; the main influence on enterprises are technical input, investment, resource consumption factors; however, all elements' transfer efficiency of assets is lower. At the same time, the capital investment of R&D also flows into the industrial scale, which is more uniform of labor factors. For Chemical Raw Materials and Chemical Products Manufacturing, the inflow of production factors mainly concentrates on resource consumption, industrial cluster scale and labor resources, and it is worth noting that the technical labor force has a large inflow in fixed assets investment, resource consumption and industrial scale. The flow of elements in Rubber

Products Industry is relatively simple. There are similar flows in both R&D capital investment and coal consumption, followed by technical personnel and labor resources is basically the same. The flow of factors in Non-Metallic Manufacturing is more focused on R&D capital investment, industrial electricity consumption, resource consumption, industry scale, and number of employees, while less focused on sales amount and total assets. In the same way, the transmission entropy distribution of the Manufacture of Special Purpose Machinery Industry is more even, and unlike the Non-Metallic Manufacturing Industry, the flow of each element to sales amount is quite obvious, and the extreme value appears in the R&D capital input and employees.

According to the results above, the relevant indicators of industrial efficiency in Jiaozuo City show a high degree of redundancy. In other words, it shows that local industries are basically in a state of high energy consumption and have not yet achieved industrial technology upgrading from basic technologies. At the same time, although capital is tilted towards technological innovation, the absence of human factors has led to an unsuccessful industrial transformation. On the one hand, due to the long-term existence of resource-based industries, its influence of radiation and assimilation on the local industrial structure is more than that of other industries that resulting in the development potential of the tertiary industry to be severely constrained especially those industries which relies on technology and residential consumption. The related technical personnel, funds, industries, and infrastructure equipment are basically in primary reserves. On the other hand, reconfiguring the labor force, especially technical personnel, requires a long period of training, which has made it difficult for many science and technology industries to maintain sustainable development. The government departments are also facing tremendous financial pressure which has led directly to the fact that the region is still dominated by labor-intensive industries. There are no high-tech industries—such as Medical Care, Transportation, and Manufacturing—let alone technological industry cluster and scale.

5. Conclusions and Suggestion

5.1. Conclusion

The technology diffusion failed to realize, traditional industry and the new technology industry scale have changed obviously.

The scale of industry is a key indicator to measure whether industry has changed or not. Extending this view, when a mineral resource-exhausted city is in a key stage of industrial transformation, there will be a large number of old-style enterprises and temporary weak new enterprises. In addition, due to the differences in new and old industrial structure and organizational form, under the prerequisite of labor force, the quantity of enterprises will change to some extent. This research shows that the K-entropy of some factors of science and technology industry in the traditional sense is lower, indicating that the development of new technology industry is being suppressed in Jiaozuo in the case of increasing human resource costs.

Furthermore, the official definition of technology-oriented industry and resource-type industry is not applied to Jiaozuo, the reason is that there are barriers in embedding technology-based industries and guaranteeing the quantity and quality of production factors required by technology industry.

By calculating the Pearson correlation coefficient, the similarity degree of production factors in different representative industries is analyzed to indirectly reflect the similarity of industrial production factor collocation.

The results show that the similarity of production factors in all industries is diverging while some industries are partially similar. It means that their development trajectory follows a 'similar-derived-differentiated' volatility model. In the initial stage of adjustment, for the solidification of industrial development models, the allocation of factors in various industries is difficult to distinguish, but along with the adjustment of industrial structure, the flow of production factors also changes that results in big fluctuations and precipitating different element configurations. Therefore, it can be considered that if there is an adjustment in the industrial structure, the corresponding factor configuration must fluctuate.

The color map of transfer entropy reveals which elements are most effective in collaboration.

What stands out is that most of the investment in R&D has formed a good flow. In other words, in the economic system of Jiaozuo, the input flow channels of R&D elements are relatively smooth, while R&D personnel in some industries and the total labor force has mutual information transfer with each other. That means the human resources quality of regional industries has a potential to increase but the stock is not enough. On the other hand, it may be due to the adjustment of industrial structure, the direction of factor inflow is still related to the original development model, such as the resource consumption.

5.2. Suggestion

Equipped with these findings, we offer two key suggestions:

First, optimize the existing workforce structure through the introduction and application of new technologies.

China should draw on some successful experience of industrial transformation of foreign mineral resources-exhausted cities to gradually achieve a sustainable industry and workforce by adopting in the early-term government nurture—in the medium-term introduce the outstanding personnel—at late stage put forward interaction between old and new industries. With the aid of technology transfer and dissemination, and constantly accelerating the training of labor skills, we might gradually form a distinctive regional industrial strategic alliance to ensure the balance among various input factors within the regional economic system, and then optimize the efficiency of labor force level and the contribution to regional economic growth.

Second, upgrade the capital investment of new technology industry to realize the substitution of new technology industry to traditional mineral resources industry, to optimize the regional input structure, to invest in new technology industry according to its characteristics, and to implement 'supply side reform'.

For resource-exhausted cities with a relatively single industrial structure, it is necessary to ensure the upgrading and optimization of the regional industrial structure, so we should not only increase the cultivation of successive industries, but also support the emerging technology industries. Local governments and banks should support the new technology industry through policies or other financial levers in order to encourage their development, increase the diffusion rate of new technologies, and ultimately achieve the goal of sustainable development within regional economic systems.

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References

1. Behrens, A.; Giljum, S.; Kovanda, J.; Niza, S. The material basis of the global economy: Worldwide patterns of natural resource extraction and their implications for sustainable resource use policies. *Ecol. Econ.* **2007**, *64*, 444–453. [CrossRef]
2. Terama, E.; Milligan, B.; Jiménez-Aybar, R.; Mace, G.M.; Ekins, P. Accounting for the environment as an economic asset: Global progress and realizing the 2030 Agenda for Sustainable Development. *Sustain. Sci.* **2016**, *11*, 945–950. [CrossRef] [PubMed]
3. Klessmann, C.; Rathmann, M.; De Jager, D.; Gazzo, A.; Resch, G.; Busch, S.; Ragwitz, M. Policy options for reducing the costs of reaching the European renewables target. *Renew. Energy* **2013**, *57*, 390–403. [CrossRef]

4. Benkovic, S.; Kruger, J. To Trade or Not to Trade? Criteria for Applying Cap and Trade. *Sci. World J.* **2014**, *1*, 953–957. [CrossRef]
5. Daskalakis, G. Temporal restrictions on emissions trading and the implications for the carbon futures market: Lessons from the EU emissions trading scheme. *Energy Policy* **2018**, *115*, 88–91. [CrossRef]
6. Bernard, A.; Haurie, A.; Vielle, M.; Viguier, L. A two-level dynamic game of carbon emission trading between Russia, China, and Annex B countries. *J. Econ. Dyn. Control* **2008**, *32*, 1830–1856. [CrossRef]
7. Springmann, M. A look inwards: Carbon tariffs versus internal improvements in emissions-trading systems. *Energy Econ.* **2012**, *34*, S228–S239. [CrossRef]
8. Mishra, T.; Parhi, M.; Diebolt, C. Human capital accumulation and spatial TFP interdependence. *Hist. Soc. Res.* **2008**, *33*, 346–358.
9. Binglian, L. Source Identification and Dynamic Evolution of Regional Economic Growth Performance in China: Based on In-put Decompositon. *Econ. Res. J.* **2006**, *4*, 90–96.
10. Lagos, R. A Model of TFP. *Rev. Econ. Stud.* **2006**, *73*, 983–1007. [CrossRef]
11. Xianxiang, X.; Yuan, S. A Dual Approach to the Growth Accounting in China. *Stat. Res.* **2009**, *26*, 78–86.
12. Yongze, Y.; Xianzhen, Z. The Factor Endowments, the Suitable Innovation Mode Selection and TFP Improvements. *Manag. World* **2015**, *9*, 13–31, 187.
13. Auty, R.M. Economic Development and the Resource Curse Thesis. In *Economic and Political Reform in Developing Countries*; Palgrave Macmillan: London, UK, 1995.
14. Lanjouw, J.O.; Mody, A. Innovation and the international diffusion of environmentally responsive technology. *Res. Policy* **1996**, *25*, 549–571. [CrossRef]
15. Aghion, P.; Harris, C.; Vickers, J. Competition and Growth with Step-by-Step Innovation: An Example. *Eur. Econ. Rev.* **1997**, *41*, 771–782. [CrossRef]
16. Sadorsky, P. Do urbanization and industrialization affect energy intensity in developing countries? *Energy Econ.* **2013**, *37*, 52–59. [CrossRef]
17. Zhang, H.; Lahr, M.L. Can the Carbonizing Dragon be Domesticated? Insights from A Decomposition of Energy Consumption and Intensity in China, 1987–2007. *Econ. Syst. Res.* **2014**, *26*, 119–140. [CrossRef]
18. Madlener, R.; Alcott, B. Energy rebound and economic growth: A review of the main issues and research needs. *Energy* **2009**, *34*, 370–376. [CrossRef]
19. Jürg, M. Lessons for Problem-Solving Energy Research in the Social Sciences. In *Tackling Long-Term Global Energy Problems*; Springer: Amsterdam, The Netherlands, 2012.
20. Santarius, T. Energy efficiency, human behavior, and economic growth: Challenges to cutting energy demand to sustainable levels. In Proceedings of the AIP Conference Proceedings AIP Publishing LLC 4th International Congress in Advances in Applied Physics and Materials Science (APMAS 2014), Fethiye, Turkey, 24–27 April 2014; Volume 1653, pp. 70–81.
21. Stiglitz, J.E.; Dasgupta, P. Industrial Structure and the Nature of Innovative Activity. *Econ. J.* **1980**, *90*, 266–293.
22. Chunhui, G.; Ruogu, Z.; Dianfan, Y. An Empirical Study on the Effects of Industrial Structure on Economic Growth and Fluctuations in China. *Econ. Res. J.* **2011**, *5*, 4–16.
23. Peneder, M. *Structural Change and Aggregate Growth*; WIFO Working Paper; Austrian Institute of Economic Research: Vienna, Austria, 2002.
24. Hori, T.; Mizutani, N.; Uchino, T. Endogenous structural change, aggregate balanced growth, and optimality. *Econ. Theory* **2018**, *65*, 125–153. [CrossRef]
25. Colin, C. *The Conditions of Economic Progress*; Macmillan & Co., Ltd.: London, UK, 1940.
26. Su, J.; Jefferson, G.H. Differences in returns to FDI between China's coast and interior: One country, two economies? *J. Asian Econ.* **2012**, *23*, 259–269. [CrossRef]
27. Konings, J. The Effect of Direct Foreign Investment on Domestic Firms: Evidence from Firm Level Panel Data in Emerging Economies. *Econ. Transit.* **2010**, *9*, 619–633. [CrossRef]
28. Keqiang, Z.; Nengsheng, L. Analysis of Social Capital and Adjustment of Industrial Structure Based on Regional and Structural Effects. *China Soft Sci.* **2017**, *4*, 66–79.
29. Syverson, C. What Determines Productivity? *J. Econ. Lit.* **2011**, *49*, 326–365. [CrossRef]
30. Feng, C.; Wang, M.; Liu, G.C.; Huang, J.B. Sources of economic growth in China from 2000–2013 and its further sustainable growth path: A three-hierarchy meta-frontier data envelopment analysis. *Econ. Model.* **2017**, *64*, 334–348. [CrossRef]

31. Xia, C.Y.; Meloni, S.; Moreno, Y. Effects of Environment Knowledge on Agglomeration and Cooperation in Spatial Public Goods Games. *Adv. Complex Syst.* **2012**, *15*, 1250056. [CrossRef]
32. Bengtsson, M.; Kock, S. Cooperation and competition in relationships between competitors in business networks. *J. Bus. Ind. Mark.* **1999**, *14*, 178–194. [CrossRef]
33. Bloembergen, D.; Tuyls, K.; Hennes, D.; Kaisers, M. Evolutionary Dynamics of Multi-Agent Learning: A Survey. *J. Artif. Intell. Res.* **2015**, *53*, 659–697. [CrossRef]
34. Corbett, C.J.; Zhou, D.; Tang, C.S. Designing Supply Contracts: Contract Type and Information Asymmetry. *Manag. Sci.* **2004**, *50*, 550–559. [CrossRef]
35. Liu, P.; Li, Y. Analysis of permanence and extinction of enterprise cluster based on ecology theory. *Int. J. Comput. Math. Sci.* **2013**, *5*, 154–159.
36. Marll, S.D. Industry Structure Similarities, Trade Agreements, and Business Cycle Synchronization. *Gettysbg. Econ. Rev.* **2008**, *2*, 4.
37. Gomez, D.M.; Torgler, B.; Ortega, G.J. Measuring Global Economic Interdependence: A Hierarchical Network Approach. *World Econ.* **2013**, *36*, 1632–1648. [CrossRef]
38. Youwen, Z.; Jianxin, Y. From Cheap Laborer Advantage to That of Rare Elements—On the Theoretical Foundation of the New Open Strategy. *Nankai J.* **2005**, *6*, 1–8, 61.
39. Chaudhuri, S. Wage inequality in a dual economy and international mobility of factors: Do factor intensities always matter? *Econ. Model.* **2008**, *25*, 1155–1164. [CrossRef]
40. Marjit, S.; Beladi, H.; Chakrabarti, A. Trade and Wage Inequality in Developing Countries. *Econ. Inq.* **2010**, *42*, 295–303. [CrossRef]
41. Jonkers, K.; Cruz-Castro, L. Research upon return: The effect of international mobility on scientific ties, production and impact. *Res. Policy* **2013**, *42*, 1366–1377. [CrossRef]
42. Ying, L. Allocative Efficiency of Regional Production Factors among the Heterogeneous Firms—The Evidence from the Manufacturing Firms in China. *Econ. Geogr.* **2013**, *33*, 31–36.
43. Yang, M.; Yang, F.; Sun, C. Factor market distortion correction, resource reallocation and potential productivity gains: An empirical study on China's heavy industry sector. *Energy Econ.* **2018**, *69*, 270–279. [CrossRef]
44. Saito, H.; Gopinath, M. Plants' self-selection, agglomeration economics and regional productivity in Chile. *J. Econ. Geogr.* **2009**, *4*, 539–558. [CrossRef]
45. Ehrl, P. Agglomeration economies with consistent productivity estimates. *Reg. Sci. Urban Econ.* **2013**, *43*, 751–763. [CrossRef]
46. Restuccia, D. *Factor Misallocation and Development*; Working Papers; Palgrave Macmillan: Basingstoke, UK, 2013.
47. Uras, B.R. Investment composition and productivity with heterogeneous entrepreneurs. *J. Macroecon.* **2013**, *35*, 104–116. [CrossRef]
48. Mattila, T.; Lehtoranta, S.; Sokka, L.; Melanen, M.; Nissinen, A. Methodological Aspects of Applying Life Cycle Assessment to Industrial Symbioses. *J. Ind. Ecol.* **2012**, *16*, 51–60. [CrossRef]
49. Wang, H. Sustainable development and technological innovation. In Proceedings of the International Conference on Electronics, Communications and Control, Ningbo, China, 9–11 September 2011; pp. 3969–3972.
50. Zhang, X.; Qiao, K. Regional Economic Interactions in China: Knowledge Spillover or Technological Diffusion? *China Econ. Q.* **2016**, *15*, 1629–1652.
51. Granger, C.W.J. *Testing for Causality: A Personal Viewpoint*; Harvard University Press: Cambridge, MA, USA, 2001.
52. Arifin, J.; Syahruddin, N. Causality Relationship between Renewable and Non-Renewable Energy Consumption and GDP in Indonesia. *Econ. Financ. Indones.* **2011**, *59*, 1–18. [CrossRef]
53. Schreiber, T. Measuring information transfer. *Phys. Rev. Lett.* **2000**, *85*, 461–464. [CrossRef] [PubMed]
54. Ver Steeg, G.; Galstyan, A. Information transfer in social media. In Proceedings of the 21st International Conference on World Wide Web, Lyon, France, 16–20 April 2012; pp. 509–518.
55. Li, J.X.; Yang, L.; Zhang, C.; Huo, Z.M.; Chen, M.H.; Luan, X.F. Quantitative assessment of urban ecosystem services flow based on entropy theory: A case study of Beijing China. *Chin. J. Appl. Ecol.* **2018**, *29*, 987–996.
56. Kangsheng, L.; Huanda, L.; Xin, Y. Modeling for the information transfer network of fish school based on video data and information transfer entropy. *Control Theory Appl.* **2014**, *31*, 858–863.

57. Núñez, J.A.; Cincotta, P.M.; Wachlin, F.C. Information entropy. *Celest. Mech. Dyn. Astron.* **1996**, *64*, 43–53. [CrossRef]
58. Benettin, G.; Galgani, L.; Strelcyn, J.M. Kolmogorov entropy and numerical experiments. *Phys. Rev. A* **1976**, *14*, 2338–2345. [CrossRef]
59. Takens, F. *Deteeting Strange Attractors in Turbulence in Dynamical Systems and Turbulence*; Springer: Berlin, Germany, 1981; pp. 366–381.
60. Kugiumtzis, D. State Space Reconstruction Parameters in the Analysis of Chaotic Time Series—The Role of the Time Window Length. *Phys. D Nonlinear Phenom.* **1998**, *95*, 13–28. [CrossRef]
61. Rosenstein, M.T.; Collins, J.J.; Luca, C.J.D. Reconstruction Expansion as a Geometry-Based Framework for Choosing Proper Delay Times. *Phys. D Nonlinear Phenom.* **1993**, *73*, 82–98. [CrossRef]
62. Hong-guang, M.; Chong-zhao, H. Selection of Embedding Dimension and Delay Time in Phase Space Reconstruction. *Front. Electr. Electron. Eng. China* **2006**, *1*, 111–114.
63. Caţaron, A.; Andonie, R. Transfer Information Energy: A Quantitative Causality Indicator between Time Series. In Proceedings of the International Conference on Artificial Neural Networks, Alghero, Italy, 11–14 September 2017.
64. Guan, J.; Chen, K. Measuring the innovation production process: A cross-region empirical study of China's high-tech innovations. *Technovation* **2010**, *30*, 348–358. [CrossRef]
65. Caballero, R.J.; Pindyck, R.S. Uncertainty, Investment, and Industry Evolution. *Int. Econ. Rev.* **1996**, *37*, 641–662. [CrossRef]
66. Prabowo, R.; Hooghiemstra, R.; Veendirks, P.V. State Ownership, Socio-political Factors, and Labor Cost Stickiness. *Eur. Account. Rev.* **2018**, *27*, 771–796. [CrossRef]
67. Shiu, A.; Lam, P.L. Electricity consumption and economic growth in China. *Energy Policy* **2004**, *32*, 47–54. [CrossRef]
68. Li, R.; Leung, G.C.K. Coal consumption and economic growth in China. *Energy Policy* **2012**, *40*, 438–443. [CrossRef]