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Digital Economy, Factor Allocation Efficiency of Dual-Economy and Urban-Rural Income Gap

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Abstract: The digital economy has significant economic structural transformation effects and income distribution effects. This article analyzed the impacts and mechanisms of digital economy development on the efficiency of dual-economic factor allocation and the urban–rural income gap from a theoretical perspective, empirically tested by using China's provincial panel data from 2008 to 2017 and a bidirectional fixed effects model. It was found that the development of the digital economy has significantly improved the efficiency of factor allocation in the dual-economy, which has a significant improvement effect on the allocation efficiency of capital and labor. The development of the digital economy alleviates the problem of surplus labor factors and insufficient capital input in the agricultural sector by promoting nonagricultural employment and the flow of capital factors to the agricultural sector. The development of the digital economy can significantly reduce the urban–rural income gap by improving the efficiency of factor allocation in the dual-economy. The main contribution of this article is verifying that the flow of production factors triggered by the digital economy has a configuration efficiency improvement effect and further extending the economic structure effect of the digital economy to the field of distribution, examining the feasible path of optimizing the income distribution pattern of the digital economy.

Keywords: digital economy; dual-economy; nonagricultural employment; urban–rural income gap; social division of labor

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1. Introduction

From 2004 to 2022, the No. 1 central document put the issues relating to agriculture, rural areas, and farmers in the first place, indicating that the problem of unbalanced and insufficient urban and rural development caused by China's dual-economy structure is still serious and the road to rural revitalization is still heavy and long. Since the reform and opening up in 1978, China's dual-economic problem has existed for a long time, and the unbalanced development between rural and urban areas has always troubled China's economic development [1]. The long-term existence of the urban–rural dual-economy structure has led to a serious surplus of rural and agricultural labor in China, but insufficient capital investment; urban and secondary and tertiary industries are abundant in capital factor, but labor shortages are increasing, resulting in a serious factor misallocation between China's agricultural and nonagricultural sectors [2]. On the one hand, the factor misallocation of the dual-economy seriously hinders the improvement of the total factor productivity of China's economy, and on the other hand, it also hinders the transformation and upgrading of China's employment structure and the narrowing of the urban–rural income gap. Therefore, it is necessary to quantitatively evaluate the degree of factor misallocation in China's dual-economy by constructing a model and deeply explore the ways to improve the efficiency of factor allocation in the dual-economy and its impact on the income gap between urban and rural areas. According to the existing research conclusions, to break the dual-economy structure and optimize the efficiency of the factor allocation of the dual-economy, on the one hand, it is necessary to break down the barriers of the flow of production factors such as labor and capital between the agricultural and nonagricultural sectors and between urban and rural areas through institutional reform, such as promoting financial development [3], reducing intervention in agricultural product prices [4], accelerating household registration system reform [5], etc.; on the other hand, it is necessary to give full play to the important role of new technologies, new models, and new formats in creating and driving employment and optimizing the production factor allocation mode and efficiency [6] and realize the efficient and reasonable flow and reallocation of production factors between urban and rural areas and between the agricultural and nonagricultural sectors at a low institutional cost by relying on the endogenous mechanism of the market. As a new economic form leading a new round of scientific and technological revolution and industrial transformation, on the one hand, the digital economy optimizes urban and rural digital infrastructure through digital industrialization to improve the factor flow mode and expand the spatial scale of factor flow [7]. On the other hand, it promotes the deep integration of cutting-edge digital technology and the real economy through industrial digitalization and triggers the reflow and reallocation of production factors between different industrial sectors by giving full play to the substitution and complementary effects of digital technology on production factors [8], and the reflow combination of production factors means the readjustment of the income distribution pattern. Therefore, while adding new momentum to China's economic growth, will the digital economy be able to effectively promote the restructuring and upgrading of production factors between the agricultural and nonagricultural sectors (or between urban and rural areas) to improve the factor allocation efficiency of China's dual-economy? Can the development of the digital economy reduce the income gap between urban and rural areas by improving the factor misallocation of the dual-economy and then promote a more balanced and full development between urban and rural areas in China? Based on the above issues, this article focused on examining whether the inter-departmental flow of production factors triggered by the development of the digital economy can improve the efficiency of factor allocation between the agricultural and nonagricultural sectors. What impact will the income distribution pattern between the agricultural and nonagricultural sectors have on the full flow and redistribution of labor and capital between the agricultural and nonagricultural sectors. From the dual-perspectives of factor allocation efficiency and income distribution fairness, we examined the economic and social effects of digital economy development. The research content and conclusions of this article have strong generalizability to countries with a urban–rural dual structure. The reason for choosing China as the research object is because China's digital economy is developing rapidly and its urban–rural dual-economy structure is very significant. In terms of empirical data, the data selected in this article were from 2008 to 2017, which was a period of rapid development of China's digital economy and rapid urbanization. Therefore, the data from 2008 to 2017 were selected for empirical testing and have strong representativeness.

The remaining part of this paper is arranged as follows: The second part is the literature review. The third part is the assessment methods and characteristic facts of the development level of the digital economy and factor misallocation of the dual-economy in various provinces in China. The fourth part is theoretical analysis. The fifth part is the data processing and empirical research design. The sixth part is empirical results and analysis. The seventh part is the conclusions and revelations.

2. Literature Review

Firstly, the research related to the topic of this paper is the relationship between the digital economy and economic growth. The digital economy has extensively penetrated and integrated multiple social and economic fields through digital industrialization and industrial digitalization and has a wide impact on the economy and society. Existing studies have found that the digital economy can affect economic growth by promoting full market competition, improving the efficiency of supply and demand matching, improving the efficiency of resource allocation, releasing the vitality of new factors such as data, and promoting innovation and entrepreneurship. For example, Jing and Sun [9] found that the digital economy can accelerate the formation of economies of scale and scope, thereby driving rapid economic growth. The digital economy can achieve high-quality economic development by increasing entrepreneurial activity. Zhang and Wang [6] found that the development of the digital economy can boost economic growth by significantly reducing capital misallocation across regions of China, but has no significant impact on labor misallocation. Huang et al. [10] found that digital economy development driven by the Internet can increase the productivity of manufacturing firms by reducing transaction costs and promoting innovation. Bai and Yu [11], based on the conclusion of a large number of literature works focusing on the digital economy to improve enterprise production efficiency, found from another aspect that the digital economy can strengthen the level of competition between enterprises so that enterprises cannot achieve the complete pass-through of costs, thereby reducing enterprise bonus and also reducing the degree of discreteness of enterprise bonus, which has a positive effect on resource allocation efficiency.

Secondly, the research related to the topic of this paper is the impact of the digital economy on the structure of the economy. According to the existing research conclusions, the digital economy has significant economic structure effects, mainly including industrial structure effects and employment structure effects. In terms of industrial structure effects, existing studies have found that the development of the digital economy can promote industrial structure upgrading; for example, Liu and Chen [12] found that the development of the digital economy has a significant role in promoting the advanced industrial structure and rationalization of industrial structure. Bai et al. [13] found that the development of the digital economy can also significantly improve the servitization of industrial structures and the advanced structure of the service industry, but the impact on the level of industrial interaction is not significant. Liu [14] further found that the digital economy can improve the degree of coordination between industries while promoting the upgrading of industrial structure, and this is mainly achieved by promoting technological innovation and deepening the social division of labor. In terms of the employment structure effect, existing studies have found that the digital economy can promote the flow of labor to the tertiary industry, and from the perspective of the labor structure of different skill levels, the digital economy can have an upgrade effect on different skill levels and can achieve an orderly social division of labor according to different skill levels of the labor force. For example, Yang et al. [15] found that the improvement of the digital level of the industry did not promote the "polarization" of the labor structure, but would lead to the orderly and progressive upgrading of the labor force with different skill levels. Bai and Zhang [8] found that the service industry has natural complementarity with the digital economy due to its intangible, non-existent, and low-energy consumption characteristics, which leads to the shift of labor to the service sector. Wu et al. [16] further found that the digital economy can especially increase the labor demand of productive service industries and high-end service industries in the process of promoting the transfer of labor to the service sector. Tian and Zhang [7] further explored the internal mechanism of the digital economy affecting the structural transfer of labor and found that the digital economy promotes the transfer of rural low-skilled labor to nonagricultural industries through the consumer Internet and promotes the rural high-skilled labor force to nonagricultural industries through the industrial Internet, ultimately promoting an orderly social division of labor. Another part of the literature examines the impact of the digital economy from the perspective of enterprises. Sun [17] found that the digital transformation of enterprises can significantly reduce financing costs. This creates favorable conditions for enterprises to expand in scale. Malkowska [18] analyzed the impact of the digital economy on different European countries from a country analysis perspective. What is more, another part of the literature delves into the consumer Internet and industrial Internet within the digital economy, respectively, studying their impact on labor mobility and employment. Among these, existing literature on the impact of the consumer Internet on labor mobility and employment has found that networked consumption and transactions improve job flexibility, providing a large number of free work opportunities for low-skilled workers. The consumer Internet has promoted the formation of the fan economy, generating a large amount of digital consumption information and giving birth to new career types such as "Internet celebrities". Digital platforms can leverage the E-commerce consumption model to promote labor employment in impoverished rural areas [19–22]. Another part of the literature explores the impact of the development of the industrial Internet on employment. This literature finds that digital technology has a negative substitution effect on labor demand, as well as a positive productivity effect and employment creation effect. Therefore, the technological changes brought about by the development of the digital economy can trigger synchronous changes in labor supply and demand through substitution effects and employment creation effects [23–29].

Finally, the research related to this paper is the study of the income distribution effect of the digital economy. Behind the impact of the digital economy on the industrial structure and employment structure, in essence, is the reflow and combined allocation of production factors such as capital and labor, and the recombination of production factors will inevitably act on the income distribution pattern. Combined with the current background of China's solid promotion of common prosperity, some scholars have discussed the relationship between the digital economy and common prosperity, and most scholars realize that the digital economy may be a "double-edged sword" for common prosperity, as follows: Jiang and Kang [30] believe that the digital economy can promote common prosperity by improving social production efficiency and enriching the social life of social members. However, attention should also be paid to the potential risks and challenges it may pose to the socio-economic situation. Liang and Lai [31] believe that the digital economy can promote multi-dimensional balanced social and economic growth through the industrial dispersion effect and market integration effect, but the digital divide and digital platform monopoly may hinder the realization of the goal of common prosperity. Other scholars have explored the impact of the digital economy on the income gap between urban and rural areas. For example, Chen and Duan [32] found that the digital economy can narrow the income gap between urban and rural areas through the market integration effect and modular division of labor effect. Liu Wei et al. [33] took digital financial inclusion as the research object and found that digital financial inclusion can narrow the income gap between urban and rural areas by eliminating relative poverty. Bai and Zhang [7] found that the development of the digital economy weakens the relative income rights of low- and middle-skilled workers, and the negative effect of the digital economy on the rights and interests of low-skilled workers is more significant in the context of the decline in demographic dividend.

The above literature provides rich and profound insights for an in-depth understanding of the economic structure effect and income distribution effect of the digital economy, but its inadequacies mainly lie in the following: First, although the improvement of resource allocation efficiency is one of the important ways to promote economic growth, the existing research is relatively weak from the perspective of resource allocation when discussing the relationship between the digital economy and economic growth, and few studies involve the research perspective of dual-economic factor allocation efficiency. Second, when studying the impact of the digital economy on the economic structure (industrial structure, employment structure), the existing literature does not extend its research content to the field of income distribution to explore how the economic structure effect of the digital economy will affect the income distribution pattern. Third, when studying the labor mobility caused by the digital economy, the existing literature agrees that the digital economy will make the labor flow from agricultural to nonagricultural industries or from agriculture and the secondary industry to the tertiary industry, but does not further answer whether the labor flow caused by the digital economy is efficient or inefficient from the perspective of factor allocation efficiency, that is it does not answer whether this labor flow ultimately optimizes or worsens the factor allocation efficiency.

Compared with the existing literature, this paper may be innovative in the following three points: Firstly, on the basis of the factor flow restructuring triggered by the digital economy, this paper further quantitatively evaluated whether the factor flow restructuring triggered by the digital economy is efficient or inefficient from the perspective of the factor allocation efficiency of the dual-economy, which provides a new research perspective for a comprehensive understanding of the factor allocation effect of the digital economy. The second is to further extend the economic structural effect of the digital economy to the field of income distribution and deeply analyze the impact of factor flow and reallocation triggered by the digital economy on the income gap between urban and rural areas. Thirdly, this paper fully draws on the basis of the calculation method of the index system for measuring the development level of the digital economy from Zhao Tao et al. [34] and Bai and Zhang [8]; the quantitative evaluation index system of digital economy development level of each province in China is constructed from the three dimensions of digital foundation, digital application, and digital innovation, and the comprehensive score of digital economy development level of each province in China is calculated by using the entropy value method, which is different from the existing literature to measure the development level of the digital economy from a single dimension or by selecting proxy variables (such as Internet development, digital inclusive finance, etc.).

3. The Characteristic Facts of the Development Level of the Digital Economy and Factor Misallocation of the Dual-Economy in Various Provinces in China

3.1. The Construction and Characteristic Facts of the Index System of the Development Level of the Digital Economy in Various Provinces in China

3.1.1. Construction of the Index System of the Development Level of the Digital Economy in Various Provinces in China

According to the main connotation of the digital economy, most of the existing studies measure the development level of the digital economy in a specific region by constructing a digital economy index system. For example, the China Academy of Information and Communications Technology (2020) divides the digital economy into four dimensions: digital industrialization, industrial digitalization, digital governance, and data value. On the basis of drawing on the methodology of the China Academy of Information and Communications Technology (2020), Bai and Zhang [8] built a digital economy development index system from four dimensions: digital industry, digital user, digital innovation, and digital platform. On the basis of fully summarizing and referring to the existing research on the construction of the digital economy index system and considering the availability and completeness of the data, this paper measured the digital economy from three perspectives: digital foundation, digital application, and digital innovation, among which the digital foundation mainly includes the construction level of fixed infrastructure and mobile infrastructure. Digital application mainly reflects the development level of digital industrialization and industrial digitalization, including digital media, digital services, and digital industrial scale; digital innovation focuses on the innovation ability and level of digital technology and mainly conducts a systematic investigation from the perspective of innovation input and innovation output. The specific tertiary indicator variables and their data sources are shown in Table 1 and will not be repeated here.

In this paper, the entropy method was mainly used to empower the subdivision index data of the Table 1 indicator system; the weights of each subdivision index were obtained, and then, the variable values of digital economy development level of each province in China from 2008 to 2017 were obtained by the weighted average method.

Table 1. Index system of digital economy development level in China's provinces.

First-Level Indicators	Second-Level Indicators	Third-Level Indicators	Data Sources
Digital foundation	Fixed infrastructure	Number of Internet broadband access ports	CEIC
		Number of Internet broadband access users	
		Number of domain names	CNNIC
		Number of sites	
		Long-distance cable line length	China Statistical Yearbook
		Local switch capacity	
	Mobile facility infrastructure	Mobile phone penetration	
		Mobile phone switch capacity	
Digital application	Digital medium	Rural broadband access users	
		Internet user penetration rate/Internet penetration rate	
		Number of computers used per 100 people	
		Number of websites per 100 businesses	
	Digital service	Proportion of enterprises engaged in E-commerce transaction activities	
		E-commerce transaction volume	
		Digital Financial Inclusion Index	Peking University Digital Financial Inclusion Index (Phase II, 2011–2018).
	Digital industry scale	Integration of informatization and industrialization development index	Evaluation report on the development level of China's integration of informatization and industrialization
		Total volume of telecommunications services	CEIC
		Software product revenue	China Statistical Yearbook
		Software business revenue	
		The number of manufacturing enterprises in the electronic information industry	
		The number of employees in the software industry	
		The number of enterprises in the software industry	
Digital innovation	Investment in innovation	R&D funding	
		Number of employed software developers	China Urban Statistical Yearbook
		Investment in fixed assets of software and information technology service industry	China Statistical Yearbook
	Innovation output	Invention patent application	
		Technology market turnover	

3.1.2. Analysis of the Characteristics of the Development Level of the Digital Economy in Various Provinces in China

Figure 1 shows the digital economy development index of each province in China from 2008 to 2017 based on the index system of the digital economy development level in Table 1 and the weighting calculation using the entropy value method. As can be seen from Figure 1, the provinces and cities in China with relatively fast and high levels of digital economy development are mainly Guangdong, Beijing, Shandong, Shanghai, Jiangsu, Zhejiang, and Fujian, and the digital economy development index scores of the above provinces and cities show a rapid growth trend; the index scores reached or exceeded 0.4 in 2017, belonging to the first echelon of China's digital economy development. The scores of the digital economy development level index of other provinces and cities are below 0.4, and their growth rate is weaker than that of the above seven provinces and cities, which indicates that China's digital economy development level varies greatly between different regions, and the imbalance of digital economy development also needs attention. According to the quantitative evaluation results obtained by the index system and calculation method of the digital economy development level in this paper, they are highly consistent with the current "China Digital Economy Development Index" released by CCID Think Tank and the "China Digital Economy Development Index (DEDI)" released by the China Academy of Information and Communications Technology, for example: in the "China Digital Economy Development Index" in 2019 released by CCID Think Tank, the top seven provinces and cities in the Digital Economy Development Index are completely consistent with the results of this article, and in the "China Digital Economy Development Index (DEDI)" in 2020 released by the China Academy of Information and Communications Technology, among the digital industrialization scale rankings, the top seven provinces and cities are also basically the same as this article, which shows that the index system and measurement methods of the inter-provincial digital economy development level constructed in this paper have strong rationality, which can objectively reflect the level and basic pattern of digital economy development in various provinces in China, which lays a good foundation for the follow-up research of this paper.

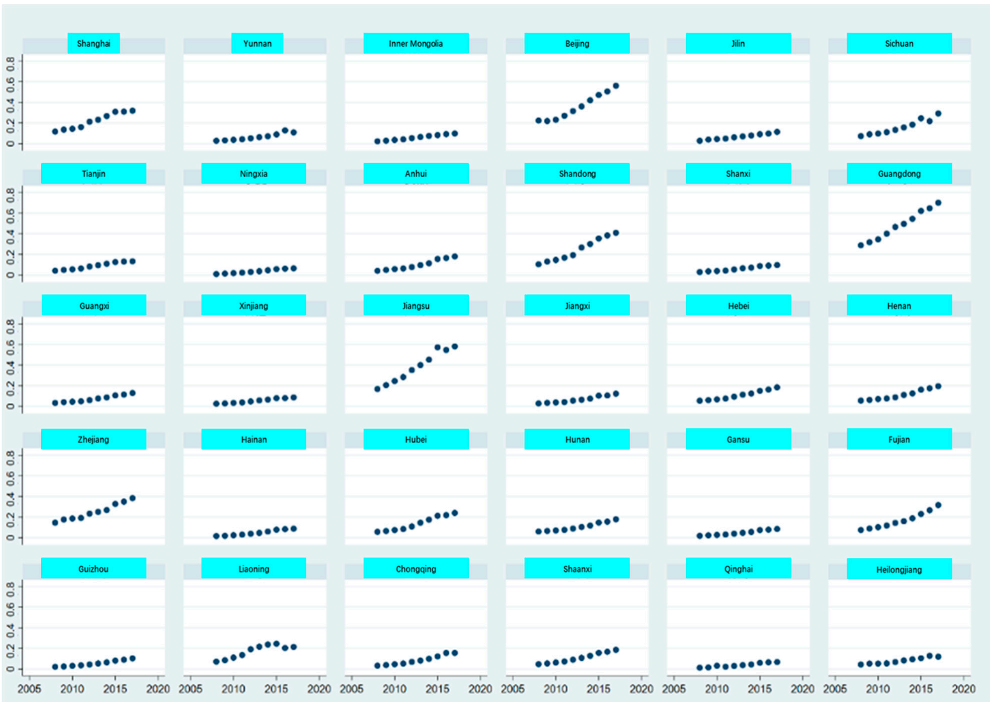

Figure 1. Schematic diagram of the change of the digital economy development index of each province in China. Data source: the authors calculated and plotted according to the indicator system in Table 1.

3.2. The Construction and Characteristic Facts of Quantitative Evaluation Model of the Factor Misallocation Level of the Dual-Economy in Various Provinces of China

3.2.1. Construction of Quantitative Evaluation Model of Misallocation Level of Binary Economic Factors in Various Provinces of China

This article refers to the model construction ideas of Brandt et al. [35], Jin [36], and Guo and Zhang [37] and, on the basis of their basic theoretical framework, further drew on the model design of Dong et al. [38]; the original assumption of constant return on the scale of the production function is further relaxed, that is the return on the scale of the department and the overall production function was no longer assumed. Suppose that the economy is composed of two major industrial sectors (i.e., the agricultural sector and the nonagricultural sector; the same below), and the output of the agricultural sector and that of the nonagricultural sector cooperate with each other to obtain the total output Y, that is Y is the CES production function of Y_i (the annual output of industry i), which is expressed as:

$$Y = (\sum_{i=1}^{N} \theta_i Y_i^{\varnothing})^{\frac{1}{\varnothing}} \tag{1}$$

where Y represents the total output and Y_i represents the output of the ith sector. $\sum_{i=1}^{N} \theta_i = 1$. θ_i is the weight of the output of sector i in the production process of total output, and its specific value can be obtained endogenously through the derivation of the later model. Suppose that the sum of sectoral input factors is the total sum of production factors, i.e., $L = \sum_{i=1}^{N} L_i, K = \sum_{i=1}^{N} K_i$, where L is labor and K is capital stock. It continues to assume that total economic output is a function of labor and capital input, $Y = AK^{\alpha}L^{\beta}$, which breaks through the assumption that the scale return is constant in the quantitative evaluation of resource allocation efficiency in previous literature. At the same time, the output of the agricultural and nonagricultural subsectors is a function of labor and capital input in each subsector, $Y_i = A_i K_i^{\alpha} L_i^{\beta}$. Therefore, the overall economic efficiency calculation formula is

$$A = (\sum_{i=1}^{N} \theta_i Y_i^{\varnothing})^{\frac{1}{\varnothing}} / K^{\alpha} L^{\beta} = [\sum_{i=1}^{N} \theta_i (A_i k_i^{\alpha} l_i^{\beta})^{\varnothing}]^{\frac{1}{\varnothing}} \tag{2}$$

This paper uses $r\tau_{K_i}$ to represent the actual financing cost of sector i, that is the price of R&D capital, and τ_{K_i} represents the distortion coefficient of capital prices between sectors. Similarly, $\omega\tau_{L_i}$ represents the labor cost of sector i, and τ_{L_i} represents the distortion coefficient of labor input prices between sectors.

Referring to the practice of the existing literature, this paper used the loss of efficiency to measure the loss of output due to resource misallocation. The loss of innovation efficiency due to resource misallocation is calculated as follows:

$$d = A^{*}/A - 1 \tag{3}$$

where A^* is the production efficiency without resource price distortion and A is the production efficiency under the existence of resource price distortion. From the above assumptions, it can be seen that, to calculate the degree of resource misallocation between the dual-economy sectors, the most-important thing is to calculate the proportion of factor inputs li and ki in the agricultural and nonagricultural sectors in the distorted state (that is, the actual state) and the non-distorted state.

The problem of maximizing the overall profit of economic activity in our country can be expressed as:

$$\max_{Y_i} \left\{ P \left(\sum_{i=1}^{N} \theta_i Y_i^{\varnothing} \right)^{\frac{1}{\varnothing}} - \sum_{i=1}^{N} P_i Y_i \right\} \tag{4}$$

where P_i represents the price of the output of the ith sector. Its first-order condition is

$$\theta_i P (\sum_{i=1}^{N} \theta_i Y_i^{\varnothing})^{\frac{1}{\varnothing}-1} Y_i^{\varnothing-1} - P_i = 0 \tag{5}$$

On the basis of this, we can obtain that $\theta_i P(\frac{Y_i}{Y})^{\varnothing-1} = P_i$, and combining the definition of Y, we can obtain that

$$P = (\sum_{i=1}^{N} \theta_i^{\frac{1}{1-\varnothing}} P_i^{\frac{\varnothing}{\varnothing-1}})^{\frac{\varnothing-1}{\varnothing}} \tag{6}$$

The problem of profit maximization in the agricultural and nonagricultural sectors can be expressed as:

$$\max_{K_i, L_I} \left\{ P_i A_i K_i^{\alpha} L_i^{\beta} - r\tau_{K_i} K_i - \omega\tau_{L_i} L_i \right\} \tag{7}$$

The first-order condition is:

$$\alpha P_i A_i K_i^{\alpha-1} L_i^{\beta} = r\tau_{K_i} \tag{8}$$

$$\beta P_i A_i K_i^{\alpha} L_i^{\beta-1} = \omega\tau_{L_i} \tag{9}$$

From this, it can be deduced that

$$\frac{K_i}{L_i} = \frac{\alpha\omega\tau_{L_i}}{\beta r\tau_{K_i}} \tag{10}$$

Now, bring Equation (10) back to Equation (9):

$$L_i = \left[P_i A_i (\frac{\alpha}{r\tau_{K_i}})^{\alpha} (\frac{\beta}{\omega\tau_{L_i}})^{1-\alpha} \right]^{\frac{1}{1-\alpha-\beta}} \tag{11}$$

Similarly, the expression of K_i can be obtained as

$$K_i = \left[P_i A_i (\frac{\alpha}{r\tau_{K_i}})^{1-\beta} (\frac{\beta}{\omega\tau_{L_i}})^{\beta} \right]^{\frac{1}{1-\alpha-\beta}} \tag{12}$$

$\frac{1}{1-\phi}$ is also the price elasticity of various differentiated product needs; therefore, $Y_i = P_i^{\frac{1}{\phi-1}}$. It can be obtained by combining (2), (11), and (12) as

$$P_i = \left[A_i (\frac{\alpha}{r\tau_{K_i}})^{\alpha} (\frac{\beta}{\omega\tau_{L_i}})^{\beta} \right]^{\frac{\phi-1}{1-(\alpha+\beta)\phi}} = \overline{A_i}^{-1} \lambda_1 \tag{13}$$

Therefore, $\overline{A_i} = \left[A_i \tau_{K_i}^{-\alpha} \tau_{L_i}^{-\beta} \right]^{\frac{1-\phi}{1-(\alpha+\beta)\phi}}$, $\lambda_1 = \left[(\frac{r}{\alpha})^{\alpha} (\frac{\omega}{\beta})^{\beta} \right]^{\frac{1-\phi}{1-(\alpha+\beta)\phi}}$. Substituting (10) into $Y_i = A_i K_i^{\alpha} L_i^{\beta}$, it can be obtained that

$$Y_i = A_i (\frac{\alpha}{r\tau_{K_i}})^{\alpha} (\frac{\omega\tau_{L_i}}{\beta})^{\alpha} L_i^{\alpha+\beta} = \overline{A_i}^{\frac{1-(\alpha+\beta)\phi}{1-\phi}} \lambda_2 (\tau_{L_i} L_i)^{\alpha+\beta} \tag{14}$$

Therefore, $\lambda_2 = (\frac{r}{\alpha})^{-\alpha} (\frac{\omega}{\beta})^{\alpha}$. Combining with (1), (6), (13), and (14), it can be obtained that $\frac{P_i}{P} = \frac{\overline{A_i}^{-1} \lambda_1}{P} = \theta_i (\frac{Y_i}{Y})^{\sigma-1} = \theta_i \left\{ \frac{\overline{A_i}^{\frac{1-(\alpha+\beta)\phi}{1-\phi}} \lambda_2 (\tau_{L_i} L_i)^{\alpha+\beta}}{Y} \right\}^{\sigma-1} = \theta_i \left\{ \frac{\overline{A_i}^{\frac{1-(\alpha+\beta)\phi}{1-\phi}} \lambda_2 (\tau_{L_i} l_i)^{\alpha+\beta} L^{\alpha+\beta}}{Y} \right\}^{\sigma-1}$. Since $\sum_{i=1}^{N} l_i = 1$, therefore, when distortions exist between different sectors, the proportions of factor inputs for labor and capital input in sector i are, respectively,

$$l_i = \frac{\theta_i^{\overline{\frac{1}{(1-\varnothing)(\alpha+\beta)}}} \overline{A_i}^{\frac{\phi}{(1-\varnothing)}} \tau_{L_i}{}^{-1}}{\sum_{i=1}^{N} \theta_i^{\overline{\frac{1}{(1-\varnothing)(\alpha+\beta)}}} \overline{A_i}^{\frac{\phi}{(1-\varnothing)}} \tau_{L_i}{}^{-1}} \tag{15}$$

$$k_i = \frac{\theta_i^{\overline{\frac{1}{(1-\varnothing)(\alpha+\beta)}}} \overline{A_i}^{\frac{\phi}{(1-\varnothing)}} \tau_{K_i}{}^{-1}}{\sum_{i=1}^{N} \theta_i^{\overline{\frac{1}{(1-\varnothing)(\alpha+\beta)}}} \overline{A_i}^{\frac{\phi}{(1-\varnothing)}} \tau_{K_i}{}^{-1}} \tag{16}$$

Then, in the state of no distortion between different departments, the proportion of R&D and innovation factors in different departments can be obtained as

$$l_i^* = k_i^* = \frac{\theta_i^{\overline{\frac{1}{(1-\varnothing)(\alpha+\beta)}}} A_i^{\overline{\frac{\phi}{1-(\alpha+\beta)\phi}}}}{\sum_{i=1}^{N} \theta_i^{\overline{\frac{1}{(1-\varnothing)(\alpha+\beta)}}} A_i^{\overline{\frac{\phi}{1-(\alpha+\beta)\phi}}}} \tag{17}$$

By substituting Equations (15)–(17) into Equation (2), the overall total factor productivity A of the Chinese economy in the state of resource misallocation and the total factor productivity A^* in the state of non-misallocation can be obtained, and the degree of resource misallocation between the agricultural and nonagricultural sectors can be calculated according to Equation (3). Then, let τ_{L_i} and τ_{K_i} be equal to 1, respectively, from which the total factor productivity of the Chinese economy A^{k^*} and A^{l^*} after only correcting capital misallocation and only correcting labor misallocation can be calculated, and the capital misallocation (*dk*) and labor misallocation (*dl*) in the overall resource misallocation between China's dual-economy sectors can be obtained using the calculation idea of Equation (3).

Through the first-order condition for profit maximization in the industrial sector, we can obtain that $\tau_i^K \propto \frac{Y_i^{nor}}{K_i}$, $\tau_i^L \propto \frac{Y_i^{nor}}{L_i}$. According to the first-order condition for maximizing overall output profit, we can obtain that the computational formula of θ_i is: $\theta_i = \frac{1}{T}\sum_{t=1}^{T} \frac{P_i(t)\left[Y_i^{nor}(t)/P_i(t)\right]^{\varnothing}}{\sum_{i=1}^{N} P_i(t)\left[Y_i^{nor}(t)/P_i(t)\right]^{\varnothing}}$. This paper continues with reference to the method of Brandt and Zhu [39]: let the capital output elasticity α be equal to 0.45, and with reference to the method of Brandt et al. [35], let $\varnothing$ equal 1/3.

3.2.2. Quantitative Assessment Results of Factor Misallocation Level of the Dual-Economy in Various Provinces in China

Table 2 shows that, in 2017, the factor misallocation between the agricultural sector and the nonagricultural sector in various provinces in China was still very serious and showed strong regional heterogeneity. The total misallocation level of Beijing, Tianjin, and Heilongjiang was less than 10%, which belongs to the regions with a low factor misallocation level. The total factor misallocation of Hebei, Liaoning, Guangdong, Shanxi, Jilin, Henan, Shaanxi, Qinghai, and Ningxia was between 10% and 20%. The factor misallocation in the remaining provinces was higher than 20%, and the total factor misallocation in Hainan, Anhui, and Guizhou was higher than 40%. From the perspective of the relative level of capital misallocation and labor misallocation, the labor misallocation in Beijing, Tianjin, Shanxi, Ningxia, Gansu, Shaanxi, Sichuan, Inner Mongolia, Hubei, and Jiangxi was higher than the capital misallocation, accounting for nearly 1/3 of all provinces, and the capital misallocation in other provinces was significantly higher than the labor misallocation. It can be seen that most of the factor misallocation between the dual-economy sectors in China's provinces was caused by capital misallocation.

Table 2. Factor misallocation between agricultural and nonagricultural sectors in various provinces of China in 2017.

Province	Total Misallocation	Capital Misallocation	Labor Misallocation	Province	Total Misallocation	Capital Misallocation	Labor Misallocation
Beijing	2.07%	0.55%	1.99%	Jiangxi	30.07%	30.64%	0.48%
Tianjin	2.99%	0.92%	2.75%	Henan	18.02%	16.36%	3.72%
Hebei	15.33%	14.34%	2.72%	Hubei	29.24%	29.38%	1.49%
Liaoning	19.12%	15.05%	6.56%	Hunan	24.31%	22.55%	4.01%
Shanghai	13.01%	13.14%	0.30%	Inner Mongolia	21.95%	22.10%	1.35%
Jiangsu	45.11%	44.18%	1.01%	Guangxi	31.93%	31.44%	2.64%
Zhejiang	27.33%	26.86%	0.08%	Chongqing	21.39%	21.57%	1.13%
Fujian	23.82%	23.97%	0.01%	Sichuan	34.19%	34.82%	0.70%
Shandong	20.69%	20.09%	2.33%	Guizhou	45.47%	43.37%	4.47%
Guangdong	19.87%	19.08%	2.45%	Yunnan	25.23%	19.98%	7.91%
Hainan	74.81%	75.82%	0.21%	Shaanxi	16.99%	9.20%	10.59%
Shanxi	13.93%	0.80%	14.74%	Gansu	26.75%	11.42%	18.67%
Jilin	13.66%	10.46%	5.34%	Qinghai	17.66%	16.14%	3.46%
Heilongjiang	9.76%	9.74%	0.96%	Ningxia	19.35%	7.58%	14.95%
Anhui	40.22%	40.51%	0.03%	Xinjiang	22.35%	21.17%	3.24%

This paper used the above theoretical model to calculate the ratio of labor input (l_i) and capital input (k_i) in the distorted state (that is, the actual state) of the agricultural and nonagricultural sectors of each province and the ratio of factor input l^*_i, k^*_i of each industry in the undistorted state, by calculating the ratio of the proportion of element inputs in the distorted state and the undistorted state, $pl = l_i/l^*_i$ and $pk = k_i/k^*_i$, thereby obtaining the degree of excess or inadequacy of factor inputs in the agricultural and nonagricultural sectors in each province. The closer pl and pk are to 1 means that the actual state of labor and capital input of the industry is ideal; greater than 1 means that the factor input of the industry is in an excessive state; less than 1 means that the factor input of the industry is insufficient.

It can be seen from Table 3 that the proportion of the factor input of the agricultural and nonagricultural sectors in China's provinces in 2012 showed the following characteristics: First, except for the eight provinces of Jiangsu, Zhejiang, Fujian, Anhui, Jiangxi, Hainan, Hunan, and Sichuan, the labor factor input of the agricultural sector in the remaining 22 provinces and cities was in a state of excessive input, and the labor input of the agricultural sector in some provinces and cities was very redundant. For example, the excessive level of labor input of the agricultural sector in Beijing, Shanxi, Shaanxi, Gansu, and Ningxia was close to or exceeded 100%. How to promote the transfer of labor from agricultural and rural areas to secondary and tertiary industries in the region is the key work to promote supply-side structural reform in the future. In sharp contrast to the proportion of labor input in the agricultural sector, in 2012, all capital factor input in the agricultural sector in all provinces in China was insufficient, and the capital input gap in the agricultural sector in most provinces and cities exceeded 90%. For example, besides Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan, Jilin, Anhui, Jiangxi, Henan, etc., only a few provinces such as Beijing, Tianjin, Heilongjiang, Shaanxi, Qinghai, Ningxia, and Xinjiang had a gap of less than 90% in agricultural sector capital investment. It can be seen that the agricultural sector in most provinces in China had bottlenecks and problems of labor redundancy and insufficient capital input, which has caused serious obstacles to the technical reformation and transformation and upgrading of China's agriculture. Second, in terms of the nonagricultural sector, the nonagricultural labor factor input in Jiangsu, Zhejiang, Fujian, Hainan, Anhui, Jiangxi, and Sichuan was relatively close to the effective level, and the nonagricultural labor factor input in the other provinces was in a state of inadequacy, while the labor gap in the nonagricultural sector in many provinces exceeded 50%, which also highlights the necessity of labor transfer and flow from the agricultural sector to the nonagricultural sector.

Table 3. The ratio of factor inputs of agricultural sectors and nonagricultural sectors in China in 2012 and 2017.

Province	2012				2017			
	Agriculture		Nonagricultural		Agriculture		Nonagricultural	
	pli	*pki*	*pli*	*pki*	*pli*	*pki*	*pli*	*pki*
Beijing	1.920	0.355	0.748	1.001	1.698	0.617	0.789	1.150
Tianjin	1.758	0.355	0.728	1.021	1.688	0.577	0.759	1.181
Hebei	1.072	0.062	0.799	1.486	1.122	0.122	0.779	1.615
Liaoning	1.274	0.072	0.728	1.344	1.405	0.072	0.668	1.524
Shanghai	1.142	0.021	0.860	1.082	0.698	0.039	0.961	1.342
Jiangsu	0.708	0.060	1.062	1.668	0.557	0.060	1.203	1.908
Zhejiang	0.678	0.029	1.051	1.486	0.526	0.029	1.152	1.706
Fujian	0.718	0.019	1.072	1.698	0.678	0.021	1.092	1.807
Shandong	1.163	0.041	0.759	1.445	1.031	0.041	0.829	1.666
Guangdong	1.203	0.011	0.769	1.354	1.041	0.011	0.839	1.565
Hainan	0.870	0.029	0.961	2.142	0.678	0.060	1.274	2.645
Shanxi	2.041	0.213	0.496	1.163	2.546	0.779	0.445	1.150
Jilin	1.163	0.041	0.728	1.536	1.354	0.213	0.647	1.534
Heilongjiang	1.284	0.243	0.708	1.264	0.991	0.193	0.870	1.534
Anhui	0.728	0.039	1.122	2.001	0.668	0.019	1.183	2.150
Jiangxi	0.870	0.011	0.940	1.708	0.789	0.011	1.021	1.938
Henan	1.152	0.062	0.728	1.536	1.173	0.112	0.728	1.666
Hubei	1.122	0.021	0.748	1.617	0.910	0.011	0.910	1.857
Hunan	0.971	0.032	0.860	1.728	1.132	0.062	0.728	1.777
Inner Mongolia	1.183	0.072	0.698	1.567	0.940	0.072	0.890	1.827
Guangxi	1.142	0.001	0.688	1.779	1.001	0.021	0.819	1.979
Chongqing	1.264	0.082	0.688	1.425	0.910	0.041	0.910	1.736
Sichuan	0.890	0.019	0.930	1.839	0.809	0.001	1.011	2.029
Guizhou	1.617	0.009	0.355	1.627	1.051	0.029	0.769	2.039
Yunnan	1.526	0.041	0.476	1.516	1.365	0.082	0.587	1.696
Shaanxi	1.920	0.112	0.415	1.304	1.708	0.223	0.526	1.443
Gansu	1.950	0.092	0.344	1.354	1.950	0.193	0.375	1.474
Qinghai	1.354	0.173	0.668	1.314	1.163	0.092	0.759	1.605
Ningxia	2.253	0.193	0.355	1.203	2.001	0.264	0.445	1.383
Xinjiang	1.324	0.122	0.627	1.466	1.092	0.072	0.769	1.767

In 2017, the state of labor and capital input in the agricultural and nonagricultural sectors did not improve to a great extent, and even the degree of labor redundancy in the agricultural sector increased in some provinces, such as Hebei, Liaoning, Shaanxi, and Jilin. Capital input in the agricultural sector in all provinces was still in a state of serious inadequacy, which also indicates that, after nearly a decade of efforts, the state of labor redundancy and insufficient capital input in China's agricultural sector had not improved. The labor and capital input of the nonagricultural sector in China's provinces had not changed much compared with 2012, which is also manifested as insufficient labor input and excessive capital investment in the nonagricultural sector in most provinces, and the excessive level of capital input has increased, which also matches the thought of the current prevention of the disorderly expansion of capital advocated by China; the excessive investment of capital in the nonagricultural sector has led to a series of socio-economic problems, and the agricultural sector has always had obstacles in technical reformation and transformation and upgrading because of the lack of capital input.

4. Model Construction and Theoretical Analysis

4.1. The Impact of the Digital Economy on the Factor Allocation Efficiency of the Dual-Economy

With reference to Hsieh and Klenow [40] and Berthold et al. [41], we established a general equilibrium model of a closed economy under the influence of the digital economy based on the dual-economy structure, focusing on how the digital economy affects the efficiency of factor allocation in the dual-economy. In order to highlight the dual-economy structure of the agricultural and nonagricultural sectors, when constructing the model, this paper focused on setting the economy in the model to include two major sectors, namely the agricultural sector and the nonagricultural sector. The total output function of the economy is determined by the CES production function:

$$Y = \left[\xi^{1/\varepsilon} Y_i^{(\varepsilon-1)/\varepsilon} + (1-\xi)^{1/\varepsilon} Y_{-i}^{(\varepsilon-1)/\varepsilon}\right]^{\varepsilon/(\varepsilon-1)} \quad (18)$$

where ξ represents the weight of agricultural sector i in the production process of the economy, ε represents the elasticity of product substitution between the agricultural sector and the nonagricultural sector, and $j = \{i, -i\}$ represents the agricultural sector and the nonagricultural sector $-i$. Assuming that there is no distortion in the price of the output between the agricultural and nonagricultural sectors, the problem of maximizing profits for the economy's overall output can be expressed as:

$$\max_{Y_j}\{P[\xi^{1/\varepsilon} Y_i^{(\varepsilon-1)/\varepsilon} + (1-\xi)^{1/\varepsilon} Y_{-i}^{(\varepsilon-1)/\varepsilon}]^{\varepsilon/(\varepsilon-1)} - P_i Y_i - P_{-i} Y_{-i}\}$$

where P is the total price index, and the first-order conditions associated with it are:

$$\frac{Y_i}{Y_{-i}} = \frac{\xi}{1-\xi}\left(\frac{P_i}{P_{-i}}\right)^{-\varepsilon} \quad (19)$$

Since this paper only studied factor price distortions at the agricultural and nonagricultural sector levels, the economic output of the agricultural and nonagricultural sectors is expressed as the enterprise production function. Defining factor capital output elasticity as $\theta_j = (\partial Y_j/\partial K_j)/(Y_j/K_j)$, it can be understood that θ_j is the output share of capital and $1-\theta_j$ is the output share of labor. Thus, the production function of the agricultural sector and the nonagricultural sector with the constant returns to scale is as follows:

$$Y_j = A_j(D_j{}^{\gamma} K_j)^{\theta_j}(D_j{}^{\delta} L_j)^{1-\theta_j} \quad (20)$$

Among these, D_j is the level of digital economy development, γ and δ, respectively, indicate the impact of digital economic development on capital accumulation and labor in economic sectors. The problem of profit π_j maximization is:

$$\max_{K_j, L_j}\{\pi_j = P_j A_j(D_j{}^{\gamma} K_j)^{\theta_j}(D_j{}^{\delta} L_j)^{1-\theta_j} - \tau_j{}^{l} W_j L_j - \tau_j{}^{k} R_j K_j\}$$

Among these, $\tau_j{}^l$ and $\tau_j{}^k$ are the factor price distortion coefficients of labor and capital, respectively. W_j and R_j are the nominal wages and nominal interest rates, respectively, which represent the prices of labor input and capital input. Let real wages equal $w_j = W_j/P_j$ and real interest rates equal $r_j = R_j/P_j$. The corresponding first-order condition can be solved as:

$$\tau_j{}^k r_j = \theta_j \frac{Y_j}{K_j} \propto MPK_j \quad (21)$$

$$\tau_j{}^l w_j = (1-\theta_j)\frac{Y_j}{L_j} \propto MPL_j \quad (22)$$

Take as an example the method of Aoki [42] to set the level of element configuration:

$$K_j = \frac{K_j}{K}K = \frac{\frac{\tau_j^k r_j}{\tau_j^k r_j} K_j}{\sum_n \frac{\tau_n^k r_n}{\tau_n^k r_n} K_n} K \quad (23)$$

$$L_j = \frac{L_j}{L} L = \frac{\frac{\tau_j^l w_j}{\tau_j^l w_j} L_j}{\sum_n \frac{\tau_n^l w_n}{\tau_n^l w_n} L_n} L \quad (24)$$

Let $\tilde{\tau}_j^k = \frac{1}{\tau_j^k}$ and $\tilde{\tau}_j^l = \frac{1}{\tau_j^l}$, and the output share of the economic sector j and its weighted share are expressed as $\varphi_j = Y_j/Y$ and $\overset{\sim}{\theta} = \sum_j \theta_j \varphi_j$, respectively, so that it can be further obtained that the factor allocation levels of capital and labor under competitive equilibrium are:

$$K_j = \frac{\theta_j \varphi_j}{\overset{\sim}{\theta}} \tilde{k}_j K \quad (25)$$

$$L_j = \frac{(1-\theta_j)\varphi_j}{1-\overset{\sim}{\theta}} \tilde{l}_j L \quad (26)$$

It is not difficult to find that the level of factor allocation is directly proportional to the relative factor price distortion and weighted factor output elasticity.

Continue to define $k_i = K_i/K$, $l_i = L_i/L$, which represents the share of capital and labor in the agricultural sector i, respectively. According to the calculation of the Pareto-optimal conditions under general equilibrium:

$$\left(\frac{\tau_i^k}{\tau_i^l}\right)\left(\frac{R_i}{W_i}\right)\left(\frac{k(\tau_i^k)_i}{1-k(\tau_i^k)_i}\right)\left(\frac{\theta_{-i}}{1-\theta_{-i}}\right) = \left(\frac{\tau_{-i}^k}{\tau_{-i}^l}\right)\left(\frac{R_{-i}}{W_{-i}}\right)\left(\frac{l(\tau_i^l)_i}{1-l(\tau_i^l)_i}\right)\left(\frac{\theta_i}{1-\theta_i}\right) \quad (27)$$

The above equation gives the relationship between the level of factor price distortion, factor allocation, and factor output elasticity. Along with Equation (22):

$$\boldsymbol{LHS} = \boldsymbol{RHS} \quad (28)$$

$$\boldsymbol{LHS} = \left(\frac{\tau_i^l}{\tau_{-i}^l}\right)\left(\frac{W_i}{W_{-i}}\right)\frac{l(\tau_i^l)_i{}^{[1-(1-\theta_i)(1-1/\varepsilon)]}}{[1-l(\tau_i^l)_i]^{[1-(1-\theta_{-i})(1-1/\varepsilon)]}}$$

$$\boldsymbol{RHS} = \Omega \cdot \frac{D_i{}^{[\gamma\theta_i+\delta(1-\theta_i)](1-1/\varepsilon)}}{D_{-i}{}^{[\gamma\theta_{-i}+\delta(1-\theta_{-i})](1-1/\varepsilon)}} \frac{k(\tau_i^k)_i{}^{\theta_i(1-1/\varepsilon)}}{[1-k(\tau_i^k)_i]^{\theta_{-i}(1-1/\varepsilon)}} \left(\frac{K}{L}\right)^{(\theta_i-\theta_{-i})(1-1/\varepsilon)}$$

Therefore, $\boldsymbol{\Omega} = \left(\frac{A_i}{A_{-i}}\right)^{(\varepsilon-1/\varepsilon)} \left(\frac{\xi}{1-\xi}\right)^{1/\varepsilon} \left(\frac{1-\theta_i}{1-\theta_{-i}}\right)$. The full differential parallelism of the two equations obtains the comparative equilibrium relationship between the development levels of the digital economy of factor price distortion as follows:

$$\frac{dln\tau_i^k}{dlnD_i} = \boldsymbol{A} \cdot [(\gamma-\delta)(\theta_i-\theta_{-i}) + (1-e)(\gamma\theta_{-i}+\delta(1-\theta_{-i}))] \quad (29)$$

$$\frac{dln\tau_i^l}{dlnD_i} = \boldsymbol{B} \cdot [(\gamma-\delta)((1-\theta_i)-(1-\theta_{-i})) + (1-e)(\gamma\theta_{-i}+\delta(1-\theta_{-i}))] \quad (30)$$

Therefore,

$$\begin{cases} e_i = dlnD_{-i}/dlnD_i \\ \boldsymbol{A} = \frac{(1-1/\varepsilon)[l_i/(1-l_i)]}{\Omega_l[k_i/(1-k_i)]+\Omega_k[l_i/(1-l_i)]} \\ \boldsymbol{B} = \frac{(1-1/\varepsilon)[k_i/(1-k_i)]}{\Omega_l[k_i/(1-k_i)]+\Omega_k[l_i/(1-l_i)]} \end{cases}$$

$$\begin{cases} \Omega_l = \{(1-l_i)(1-\theta_i)(1-1/\varepsilon) - l_i[1-(1-\theta_{-i})(1-1/\varepsilon)]\}/(1-l_i) \\ \Omega_k = [(1-k_i)(1-1/\varepsilon)\theta_i + k_i(1-1/\varepsilon)\theta_{-i}]/(1-k_i) \end{cases}$$

In the above formula, e represents the relative level of the development of the digital economy of the two economic sectors (agricultural sector and nonagricultural sector) and $(\gamma\theta_{-i} + \delta(1 - \theta_{-i}))$ indicates the weighted factor output level of the digital economy in the nonagricultural sector $-i$, and there is exactly $\Omega_{\boldsymbol{k}}, \Omega_{\boldsymbol{l}} > 0$, $\boldsymbol{A}, \boldsymbol{B} > 0$ (the production function has the constant factor elasticity of scale return $\theta_i \in (0, 1)$). Further simplification shows that factor price distortions can actually be influenced by changing e the relative marginal output ratio of factors between the two economic sectors. For agricultural sector i, the impact of the level of digital economy development on the price distortion of capital factors depends on the positive or negative of $[(\gamma - \delta)(\theta_i - \theta_{-i}) + (1 - e)(\gamma\theta_{-i} + \delta(1 - \theta_{-i}))]$ and the value of e.

The above model derivation shows that product substitution elasticity $\varepsilon = 1$ if there is no difference in output between the agricultural and nonagricultural sectors. At this point, the impact of the digital economy on factor price distortions is zero. However, because there are obvious differences in products between China's agricultural sector and nonagricultural sector in reality, that is it can be considered that $1/\varepsilon < 1$ in the model parameters. From this analysis, we can see the following:

(1) If $e = 1$, that is there is no difference in the level of digital economy development between the two sectors of the economy (for example, if there is a common market between two economic sectors), it is advisable to assume $\theta_i > \theta_{-i}$ (According to symmetry, the result is the same when $\theta_i < \theta_{-i}$.), that is agricultural sector i has a higher elasticity of capital output. At this time, if the digital economy D_j has a greater impact on capital ($\gamma > \delta$), it will make τ_i^k rise and τ_i^l fall, and vice versa. That is, when the level of digital economy development between the agricultural and nonagricultural sectors coincides, the development of the digital economy may increase the flow of capital into agricultural sector i with higher factor output, thereby increasing the level of capital price distortion in the agricultural sector, and by contrast, it will make labor price distortions of agricultural sector i increase.

(2) If the level of digital economy development in the agricultural sector i and the nonagricultural sector $-i$ is not consistent, that is $0 < e < 1$ or $e > 1$, in the above case (we assumed that $\gamma > \delta$ and $\theta_i > \theta_{-i}$), the positive or negative symbols of $\frac{dln\tau_i^k}{dlnD_i}$ and $\frac{dln\tau_i^l}{dlnD_i}$ depend on the difference ($|\gamma - \delta|$) in the degree of impact of the digital economy on capital and labor and the difference ($|1 - e|$) in the level of digital economy development between the agricultural and nonagricultural economic sectors. For example, if the velocity of digital economy development in agricultural sector i is relatively slow, that is $e > 1$, then $(1 - e)(\gamma\theta_{-i} + \delta(1 - \theta_{-i}))$ is less than zero. When $\gamma > \delta$, there may be $\frac{dln\tau_i^k}{dlnD_i} < 0$ and $\frac{dln\tau_i^l}{dlnD_i} > 0$, that is the development of the digital economy will reduce the distortion coefficient of capital factors (τ_i^k), increase the distortion coefficient of labor factors (τ_i^l), and vice versa.

4.2. The Impact of the Change of Factor Allocation Efficiency of the Dual-Economy on the Income Gap between Urban and Rural Areas

It can be seen from the theoretical model of the second sector in this paper that, when there is distortion in the factor allocation of the dual-economy sector (that is, in the real state), the per capita income between the agricultural sector and the nonagricultural sector can be expressed as Y_i and L_i, respectively, and after correcting the factor misallocation of the dual-economy sector, the factor input ratios of the agricultural sector and the nonagricultural sector change from $l_i = \frac{\theta_i^{\frac{1}{(1-\varnothing)(\alpha+\beta)}} \overline{A_i}^{\frac{\phi}{(1-\varnothing)}} {\tau_{L_i}}^{-1}}{\sum_{i=1}^{N} \theta_i^{\frac{1}{(1-\varnothing)(\alpha+\beta)}} \overline{A_i}^{\frac{\phi}{(1-\varnothing)}} {\tau_{L_i}}^{-1}}$, $k_i = \frac{\theta_i^{\frac{1}{(1-\varnothing)(\alpha+\beta)}} \overline{A_i}^{\frac{\phi}{(1-\varnothing)}} {\tau_{K_i}}^{-1}}{\sum_{i=1}^{N} \theta_i^{\frac{1}{(1-\varnothing)(\alpha+\beta)}} \overline{A_i}^{\frac{\phi}{(1-\varnothing)}} {\tau_{K_i}}^{-1}}$ to ${l_i}^* = {k_i}^* = \frac{\theta_i^{\frac{1}{(1-\varnothing)(\alpha+\beta)}} A_i^{\frac{\phi}{1-(\alpha+\beta)\phi}}}{\sum_{i=1}^{N} \theta_i^{\frac{1}{(1-\varnothing)(\alpha+\beta)}} A_i^{\frac{\phi}{1-(\alpha+\beta)\phi}}}$, at which point, the output of the agricultural and nonagricultural sectors in the state of fully effective factor allocation becomes $Y_i^* = A_i(K_i * k_i^*/k_i)^\alpha (L_i * l_i^*/l_i)^\beta$ and their respective per capita incomes also become $\frac{Y_i^*}{L_i * \frac{l_i^*}{l_i}} = A_i\left(K_i * \frac{k_i^*}{k_i}\right)^\alpha \left(L_i * \frac{l_i^*}{l_i}\right)^{\beta-1} = \frac{Y_i}{L_i}\left(\frac{k_i^*}{k_i}\right)^\alpha \left(\frac{l_i^*}{l_i}\right)^{\beta-1}$. At this time, the urban–rural income gap when there is a factor misallocation of the dual-economy sector and the urban–rural income gap when there is no factor misallocation of the dual-economy sector can be compared.

The urban–rural income gap when there is a factor misallocation of the dual-economy sector is as follows:

$$\begin{aligned}(Y_{agriculture}/L_{agriculture})/(Y\_non-agriculture/L_{non-agriculture}) \\ = (A_{agriculture}K^{\alpha}_{agriculture}L^{\beta-1}_{agriculture}) \\ /(A_{non-agriculture}K^{\alpha}_{non-agriculture}L^{\beta-1}_{non-agriculture})\end{aligned}$$

The urban–rural income gap when there is no factor misallocation of the dual-economy sector is as follows:

$$\begin{aligned}&(Y\_agriculture/L_{agriculture})/(Y_{non-agriculture}/L_{non-agriculture}) \\ &= (A_{agriculture}K^{\alpha}_{agriculture}L^{\beta-1}_{agriculture})(\frac{k_{agriculture}{}^*}{k_{agriculture}})^\alpha(\frac{l_{agriculture}{}^*}{l_{agriculture}})^{\beta-1}/ \\ &(A_{non-agriculture}K^{\alpha}_{non-agriculture}L^{\beta-1}_{non-agriculture})(\frac{k_{non-agriculture}{}^*}{k_{non-agriculture}})^\alpha(\frac{l_{non-agriculture}{}^*}{l_{non-agriculture}})^{\beta-1}\end{aligned}$$

It can be seen from the above formula that the urban–rural income gap expression after correcting the factor misallocation of the dual-economy sector increases the factor input ratio variable between the agriculture and nonagricultural sectors compared with the urban–rural income gap expression when there is a factor misallocation of the dual-economy sector, and the change of the factor input ratio before and after correcting the factor misallocation is an important reason affecting the urban–rural income gap. It can be seen from the above formula that, when the proportion of effective capital input in the agricultural sector after correcting the factor misallocation $\left(\frac{k_{agriculture}{}^*}{k_{agriculture}}\right)$ increases, the per capita income of the agricultural sector will also increase, which, in turn, is conducive to narrowing the income gap between urban and rural areas. When the proportion of effective labor input in the agricultural sector after correcting the factor misallocation $\left(\frac{l_{agriculture}{}^*}{l_{agriculture}}\right)$ increases, because the index of this variable is $\beta - 1 < 0$, increasing the proportion of labor factor input in the agricultural sector at this time will reduce the per capita income level of the agricultural sector, thereby widening the income gap between the agricultural sector and the nonagricultural sector. Similarly, when the proportion of effective capital input in the nonagricultural sector after correcting for factor misallocation $\left(\frac{k_{non-agriculture}{}^*}{k_{non-agriculture}}\right)$ increases, the per capita income of the nonagricultural sector will also increase, and all other things being equal, it will widen the urban–rural income gap. When the proportion of effective labor input in the nonagricultural sector after correcting the factor misallocation $\left(\frac{l_{non-agriculture}{}^*}{l_{non-agriculture}}\right)$ increases, because the index of this variable is also $\beta - 1 < 0$, the increase in labor factor input in the nonagricultural sector caused by the correction of factor misallocation will reduce the per capita income level of the nonagricultural sector, which, in turn, is conducive to narrowing the income gap between the agricultural sector and the nonagricultural sector. Considering the current situation of a large amount of redundant labor force in China's agricultural and rural fields, as well as the dilemma of recruiting workers in the urban manufacturing and service industries, the factor misallocation between China's agricultural and nonagricultural sectors is likely to be caused by excessive labor input in agricultural and rural areas and insufficient labor input in nonagricultural sectors. From the perspective of capital factors, it may be the opposite, that is there is a gap in capital investment in China's agricultural and rural areas, resulting in unsatisfactory industrial automation, mechanization, and digital technology transformation and upgrading in agricultural rural areas, while there are an excessive capital investment in the nonagricultural sector and lack of willingness to flow to the agricultural sector, eventually resulting in capital misallocation between the dual-economy sectors. Based on the above characteristic reality, this paper further constructed a quantitative evaluation model of the factor allocation efficiency between the dual-economy sectors and used China's provincial-level data to empirically evaluate whether the factor misallocation of the dual-economy in China meets the above characteristics. If the theoretical model constructed in this section is consistent with the empirical analysis results, then correcting the factor misallocation of the dual-economy will help narrow the income gap between the agricultural sector and the nonagricultural sector, considering that the proportion of agriculture in rural areas is significantly higher than that in urban areas, so the above impact mechanism can be further extended from the income gap between the agricultural and nonagricultural sectors to the urban–rural income gap, that is the digital economy can improve China's urban–rural income gap by correcting the factor misallocation between the dual-economy sectors.

5. Materials and Methods

5.1. Metrology Model Setting

Based on the above analysis, this paper focused on empirically testing whether the development of the digital economy can achieve the purpose of narrowing the urban–rural income gap by correcting the factor misallocation between the dual-economy sectors. Therefore, this paper needed to establish two types of econometric models: first, the econometric model of the impact of the digital economy on the efficiency of factor allocation between sectors of the binary economy; second, the impact model of factor allocation efficiency changes of the dual-economy sectors on the urban–rural income gap. The specific model settings of the first step of the empirical task are as follows:

$$mis_{it} = \alpha + \beta_1 digi_{it} + \gamma X_{it} + u_i + v_t + \varepsilon_{it} \tag{31}$$

where the subscript i represents the province and the subscript t represents the year; X_{it} represents a series of control variables; u_i represents individual fixed effects; v_t represents a time fixed effect; mis_{it} is the explained variable, which represents a factor misallocation between sectors of the dual-economy (that is, including total misallocation, as well as capital and labor misallocation); $digi_{it}$ is the core explanatory variable, indicating the level of the digital economy development of province i in year t; ε_{it} is a random perturbation term.

The second empirical task is to test whether the improvement of factor allocation efficiency between the dual-economy sectors can narrow the income gap between urban and rural areas. The specific measurement model was set as follows:

$$gap_{it} = \alpha + \beta_1 mis_{it} + \gamma X_{it} + u_i + v_t + \varepsilon_{it} \tag{32}$$

Similarly, the subscript i represents the province and the subscript t represents the year; X_{it} represents a series of control variables; u_i represents individual fixed effects; v_t represents a time fixed effect; mis_{it} is the core explanatory variable, indicating the factor misallocation between the dual-economy sectors (that is, including total misallocation, as well as capital and labor misallocation); gap_{it} is the explained variable, indicating the level of the urban–rural income gap in province i in year t; ε_{it} is a random perturbation term.

To address the potential issue of missing variables in the model as much as possible, this paper used a panel bidirectional fixed effects model for estimation. In theory, the panel bidirectional fixed effects model can solve the problem of missing variables that do not change with time, but vary with individuals and do not change with individuals, but change with time. On the one hand, the problem of missing variables is effectively solved by using a panel bidirectional fixed effects model. On the other hand, based on the use of a panel bidirectional fixed effects model, the characteristic variables of each province in China are controlled.

5.2. Data Processing and Description of Sources

Referring to the practice of Bai and Yang [1], the agricultural sector is defined as the primary industry and the nonagricultural sector is defined as the secondary and tertiary industries, and the quantitative evaluation model of factor allocation efficiency between the dual-economy sectors constructed in this paper is used to calculate the factor allocation efficiency level between the dual-economy sectors in various provinces in China. Among these, the sectoral added value, capital stock, and labor force data required in the calculation process were mainly from the China Statistical Yearbook, provincial statistical yearbooks, and the Wind database.

Sector value-added (Y), capital stock, and labor force: This paper divided the economic sector of each province into the agricultural and nonagricultural sectors. Among these, the nonagricultural sector is the secondary industry and the tertiary industry, and the added value of this sector is expressed by the sum of the added value of the secondary industry and the tertiary industry. The data used in this paper were from 2008 to 2017, and the value-added data for all sectors were deflated by the value-added price index; finally, the nominal value-added variable for each province was obtained with 2008 as the base period. Physical capital stock (K): This paper used the perpetual inventory method to calculate the physical capital stock of each province from 2008 to 2017, and the investment in fixed assets of the tertiary industries in each province was summed up by the relevant industries according to the Regulations on the Division of Three Industries in 2012; the economic depreciation rate of material capital of 9.6% was used by reference to Zhang et al. [43] for the corresponding processing, and the data of fixed asset investment was derived from the China Fixed Asset Investment Database in the EPS database and was deflated by the fixed asset investment price index. The data on the number of labor force in the three major industries of each province were based on the statistical yearbooks of each province.

Factor misallocation of the dual-economy sectors: Based on the calculation of the added value, capital stock, and labor force of the department in each province, the quantitative evaluation model of factor allocation efficiency between the dual-economy sectors constructed in this paper was used to calculate the total factor misallocation, capital misallocation, and labor misallocation level between the dual-economy sectors in Chinese provinces from 2009 to 2018.

Income gap between urban and rural areas: This paper refers to Lu and Chen [44] to use the urban–rural income ratio (gap) to characterize the urban–rural income gap in various provinces in China, that is the ratio of the per capita disposable income of urban residents to the per capita disposable income (or net income) of rural residents, and the lager the ratio is, the lager the urban–rural income gap is. The data used to calculate the urban–rural income gap in China's provinces were mainly from the provincial statistical yearbooks and the Wind database, covering the period from 2008 to 2017.

The level of digital development: This paper used the digital economy development level index system, related index data, and empowerment methods to calculate the variables of the digital economy development level in various provinces in China from 2008 to 2017. The composition of its indicators, calculation methods, and data sources are described above.

Control variables' selection: When examining the influence of the digital economy on the efficiency of factor allocation between sectors of the dual-economy, this paper selected the following control variables: (1) Marketization level variables: A large number of studies have shown that the improvement of the marketization level can significantly reduce the level of factor misallocation and improve the efficiency of factor allocation. This paper selected the market-oriented index depicted by Fan Gang; the data were derived from the Wind database, and the average annual growth rate was used to extrapolate the missing data in 2017 and 2018. (2) The level of opening up: Whether it is the improvement of import and export levels or the introduction and going out of the investment field, this will have a significant impact on China's factor allocation efficiency. The improvement of import and export levels expands the space of overseas markets, and changes in overseas demand will guide the allocation of domestic factor flows to better meet overseas demand. FDI and OFDI are the reflow and reallocation of capital on a global scale, which has the color and function of resource allocation. Therefore, when empirically testing the impact of digital economy development on the efficiency of factor allocation between sectors of the dual-economy, this paper took the proportion of the total import and export of each province of the GDP as the level of opening up to measure the level of opening up of a region and added it to the empirical model as a control variable for co-regression analysis. (3) The proportion of government financial expenditure: According to the research of Jin Laiqun et al [36], the government uses administrative monopoly power to improperly intervene in economic operation, which is one of the important reasons for the serious factor misallocation in China, and how to define the boundary between efficient market and active government is still the focus of current academic research. In this paper, the variable of government fiscal expenditure proportion was added to the empirical regression as a proxy variable for government intervention in the economy. (4) Years of education per capita: The per capita number of years of education reflects the level of human capital in a certain region, and the improvement of human capital level can enable labor factors to have broader employment choices and job choices, thereby improving the selectivity and adaptability of the combination of production factors and effectively reducing factor misallocation. In this paper, the average number of years of education per capita was put into the empirical model as a human capital proxy variable for joint regression.

In the empirical analysis of the impact of the change of factor misallocation efficiency of the dual-economy on the income gap between urban and rural areas in the second step, the control variables were selected as follows: (1) Government fiscal revenue: Government fiscal revenue represents the level of government financial resources in the region and is an important basis for the government to adjust the income distribution pattern through transfer payments. (2) Per capita GDP and the square of per capita GDP: Considering that many studies believe that there is a significant relationship between economic growth and the urban–rural income gap and the relationship is manifested as a nonlinear U-shaped or inverted U-shaped relationship, this paper introduced the per capita GDP variable and the square of per capita GDP as the control variables. (3) Urbanization level: Most of the existing literature has found that the increase of the urbanization level has a significant impact on the income gap between urban and rural areas, and its impact has a threshold effect, so this paper selected the urbanization level as the control variable. (4) Retail sales level of consumer goods: The retail sales level of consumer goods represents the smooth flow of circulation in a region and also represents the level of commercial development in the region. This paper also selected it as a control variable to add to the model for regression analysis.

In addition, in the process of empirical regression, this paper also examined the flow of production factors triggered by the digital economy to verify the intrinsic influence mechanism of the digital economy on the efficiency of factor allocation between sectors of the dual-economy, so it is also necessary to use the ratio of agricultural labor factor input, the ratio of agricultural capital factor input, the ratio of nonagricultural labor factor input, the ratio of nonagricultural capital factor input, the agricultural labor proportion, the secondary industry labor proportion, the tertiary industry labor proportion, and the nonagricultural industry labor proportion in the empirical regression process.

The descriptive statistical results of the main variables are shown in Table 4 and will not be repeated here.

Table 4. Descriptive statistical results of major variables.

Variable Meaning	*Variable*	*N*	*Mean*	*Std*	*Min*	*Max*
Urban–rural income gap	*gap*	300	1.0903	0.2036	0.6119	1.5793
Digital economy development	*digi*	300	0.1459	0.1371	0.0199	0.7174
Government revenue	*lngov*	300	−2.2245	0.2826	−2.8854	−1.4100
Marketization level	*lnmarket*	300	1.8145	0.3247	0.8644	2.3645
The level of opening up	*lnopen*	300	−1.6843	0.9666	−4.0504	0.4830
The level of urbanization	*lnurban*	300	−0.6261	0.2416	−1.2362	−0.1008
Retail sales level of consumer goods	*lnretail*	300	−0.9583	0.1722	−1.3844	−0.2955
Years of education per capita	*Edu*	300	8.5496	1.0917	5.5024	12.8017
Proportion of government expenditure	*Govpay*	300	0.2211	0.1140	0.0797	0.7756
Per capita income level	*lnAgdp*	300	10.0898	0.8281	8.0112	11.9603
The square of per capita income level	$lnAgdp^2$	300	101.2746	16.2781	63.4047	141.4080
The total factor misallocation of the dual-economy	*Mis*	300	0.2788	0.1397	0.0309	0.7713
The capital misallocation of the dual-economy	*Misk*	300	0.2350	0.1486	0.0156	0.7804
The labor misallocation of the dual-economy	*Misl*	300	0.0738	0.0753	0.0100	0.3578
The proportion of agricultural labor factor inputs	Pl_1	300	1.3980	0.4690	0.6364	3.1924
The proportion of agricultural capital inputs	Pk_1	300	0.1987	0.1455	0.0433	0.8927
The proportion of nonagricultural labor factor inputs	pli_{23}	300	0.8493	0.2329	0.3481	1.4100
The proportion of nonagricultural capital inputs	pki_{23}	300	1.5870	0.2865	1.0564	2.5667
The proportion of agricultural labor	$labratio_1$	300	0.3524	0.1344	0.0505	0.6427
The proportion of labor in the secondary industry	$labratio_2$	300	0.2913	0.0762	0.1243	0.5010
The proportion of labor in the tertiary industry	$labratio_3$	300	0.3963	0.0887	0.2565	0.7608
The proportion of nonagricultural labor	$laborratio_{23}$	300	0.6776	0.1344	0.3873	0.9795

6. Results and Discussion

6.1. The Impact of the Digital Economy on the Efficiency of Factor Allocation between Sectors of the Dual-Economy

In this paper, the two-way fixed effect model and China's provincial panel data from 2008 to 2017 were used to empirically examine the impact of the digital economy on the efficiency of factor allocation between sectors of the dual-economy. It can be seen from Table 5 that, under the condition of controlling the fixed effect of time and the individual fixed effect and adding the control variables at the same time, when the explanatory variables are total factor misallocation, capital misallocation, and labor misallocation, the regression coefficient of the core explanatory variable (digital economic development level) is significantly negative at least the 5% level. When the explanatory variable is total factor misallocation, the regression coefficient of the digital economy development level is negative at the 5% significance level. When the explanatory variable is capital misallocation, the regression coefficient of the digital economy development level is negative at the 1% significance level. When the explanatory variable is labor misallocation, the regression coefficient of the digital economy development level is negative at the 5% significance level. This shows that the development of the digital economy can indeed significantly alleviate the factor misallocation between the dual-economy sectors, and its mitigation effect is very significant, whether it is capital misallocation or labor misallocation, which also verifies the conclusion derived from the theoretical model constructed in this paper.

Table 5. Empirical regression results of the impact of the digital economy on the factor allocation efficiency of the dual-economy.

Explained Variable	Mis	Misk	Misl
digi	−0.6815 ** (−2.49)	−0.2148 *** (−3.23)	−0.1075 ** (−2.44)
Control variables	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes
Adjusted R^2	0.1737	0.3727	0.5430
Sample size	300	300	300

Note: t-values are in parentheses; ***, ** represent signiffcance at the 1%, 5% levels, respectively.

The above empirical analysis verified that the digital economy can significantly alleviate the factor misallocation between sectors of the dual-economy and improve the efficiency of factor allocation between sectors of the dual-economy. However, the empirical work performed above does not explain how the digital economy guides the reflow and reallocation of factors of production between the agricultural and nonagricultural sectors or, rather, the above empirical analysis cannot explain the characteristics of the flow of factors of production caused by the development of the digital economy. To this end, this paper continued to take the proportion of capital and labor in the agricultural and nonagricultural sectors and the proportion of capital and labor in the secondary and tertiary industries as the explanatory variables, took the development level of the digital economy as the core explanatory variable, and continued to empirically analyze the impact of the digital economy on the flow direction of production factors; at the same time, it analyzed the internal mechanism of the digital economy to alleviate the efficiency of factor allocation between the dual-economy by combining the excessive and insufficient factor inputs between the agricultural and nonagricultural sectors, as well as among the primary, secondary, and tertiary industries in various provinces in China.

Since the ratio of capital and labor of each industrial sector are continuous variables with values of (0,1), the traditional OLS regression method or bidirectional fixed effect model cannot be used for empirical research. Instead, the Tobit method should be used for regression to effectively avoid a series of regression bias problems caused by the limited value of the explanatory variables. The results obtained by using the Tobit regression model are shown in Table 6. In terms of the proportion of capital and labor input in the agricultural sector and the nonagricultural sector, when the explained variable is the proportion of labor input in the agricultural sector, the regression coefficient of the digital economy development level is negative at the 10% significance level; in contrast, when the explained variable is the proportion of labor input in the nonagricultural sector, the regression coefficient of the digital economy variable is positive at the significance level of 10%. Combined with the current situation of excessive labor input in the agricultural sector and labor shortage in the nonagricultural sector in China, the digital economy can reduce the labor input level of the agricultural sector and increase the labor input level of the nonagricultural sector by promoting nonagricultural employment and guiding the flow of labor in the agricultural sector to the nonagricultural sector. In turn, the allocation efficiency of labor factors between the agricultural sector and the nonagricultural sector is optimized. The third and fourth columns of Table 6 distinguish the nonagricultural sector into the secondary industry and the tertiary industry and, then, examine the impact of the digital economy on the internal labor flow and allocation efficiency of the nonagricultural industry. It can be seen from the third and fourth columns in the upper part of Table 6 that the digital economy has a significant negative effect on the proportion of labor in the secondary industry and a significant positive effect on the proportion of labor in the tertiary industry. Combined with the quantitative assessment results of the input status of production factors in China's three major industries, that is, in 2019, the labor factor input of the secondary industry and the tertiary industry in all provinces in China was in a state of inadequacy. It can be seen that the intangibility and flexibility of service products in the tertiary industry can be naturally coupled with the digital economy (Bai Peiwen and Zhang Yun, 2021) [8], so the factors of the tertiary industry are more biased. Combined with the current situation of insufficient labor input in the secondary industry, the labor flow of the nonagricultural sector caused by the digital economy is likely to aggravate the labor shortage problem in the secondary industry and, thus, aggravate the problem of China's economy "dematerializing from reality to virtuality", which needs to arouse our vigilance. The main reasons for the above results are that the development of the digital economy has provided a wide range of employment opportunities for low-skilled labor such as online anchors, online customer service, and couriers through digital industrialization; on the other hand, through the digitization of the industry, the demand for low-skilled labor such as selling riders and sharing bike maintenance personnel has increased. Therefore, the digital economy can drive the flow of low-skilled rural labor to the service industry.

Table 6. The impact of the digital economy on labor and capital structure in the agricultural and nonagricultural sectors.

Explained Variable	**Labratio 1**	**Labratio 23**	**Labratio 2**	**Labratio 3**
digi	−0.0583 *	0.0583 *	−0.3153 ***	0.0887 *
	(−1.78)	(1.78)	(−5.96)	(1.72)
Control variables	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.8517	0.8517	0.6226	0.8131
Sample size	300	300	300	300
Explained Variable	Capratio 1	Capratio 23	Capratio 2	Capratio 3
digi	0.0251 ***	−0.0251 ***	−0.1704 ***	0.1715 ***
	(2.58)	(−2.58)	(−3.04)	(2.99)
Control variables	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.3311	0.3311	0.3311	0.4264
Sample size	300	300	300	300

Note: t-values are in parentheses; *** and * represent signiffcance at the 1% and 10% levels, respectively.

In terms of capital factors, it can be seen from Table 6 that the digital economy has a positive and significant impact on the proportion of capital input in the agricultural sector and a negative and significant impact on the capital factor of the nonagricultural sector. This shows that the digital economy can effectively guide the flow of capital factors to the agricultural sector, thereby alleviating the problem of capital shortage in the agricultural sector and excessive capital input in the nonagricultural sector. Relevant examples can also be obtained from the actual situation: First, in the circulation link, rural E-commerce, online live streaming goods, short videos of rural cultural tourism publicity, and other online new economy and new patterns based on digital technology have created a new driving force for the transformation and development of China's rural industries. In 2021, the national rural online retail sales was CHY 2.05 trillion, an increase of 11.3% over the previous year, and the growth rate accelerated by 2.4 percentage points (data source: http://www.songyang.gov.cn/art/2022/10/31/art_1229536455_58986712.html accessed on 31 October 2022). The national online retail sales of agricultural products reached CNY 422.1 billion, a year-on-year increase of 2.8%. "Digital commerce to revitalize agriculture" has been further promoted, and the "new infrastructure" of rural E-commerce has been continuously improved. The rapid rise of new patterns and new formats such as live streaming and short video content has made agriculture and rural areas the main battlefield for its key content mining, which has not only shaped a number of rural and agricultural products' Internet celebrity IP brands, but also driven the sales of agricultural products and their surrounding value-added services (such as rural tourism and other value-added services). Second, in the production and manufacturing links, the development of the digital economy has accelerated the digital transformation of the circulation link and, then, forced the transformation of the production mode of the agricultural sector, such as: the digitalization and intelligence of agricultural enterprises such as Hema and Qingmei are accelerating, so as to effectively meet the scale flow effect formed by the digital transformation of the circulation link.

From the perspective of capital flow within the nonagricultural sector, the digital economy can significantly reduce the proportion of capital factors in the secondary industry and significantly increase the proportion of capital factors in the tertiary industry. According to the results of Section 4, in 2019, the problem of excessive capital input in the tertiary industry in various provinces in China was more serious than that in the secondary industry. The investment status of tertiary industry capital factors in Beijing, Tianjin, Hebei, Inner Mongolia, Jilin, Jiangsu, and Gansu was basically close to the effective level; the tertiary industry capital factors in Shanxi and Heilongjiang were in a state of significant underinvestment; the tertiary industry capital factors in the remaining 21 provinces were in a significant state of excess. In contrast, in 2019, the capital factor input of the secondary industry in Liaoning, Heilongjiang, Jiangsu, Jiangxi, Shandong, and Gansu was in a serious state of excess, and nearly 14 provinces were in a state of serious inadequacy. Therefore, the flow of capital factors from the secondary industry to the tertiary industry triggered by the digital economy may essentially aggravate the excessive capital investment of the tertiary industry and the insufficient capital investment of the secondary industry, thereby worsening the capital allocation efficiency among the three major industries.

In summary, the digital economy can alleviate the misallocation of labor factors between the dual-economy sectors by guiding the flow of labor from the agricultural sector to the nonagricultural sector and driving nonagricultural employment. It can alleviate the problem of the insufficient capital input of the agricultural sector and the excessive capital factor input of the nonagricultural sector by guiding the flow of capital factors to the agricultural sector and, then, optimize the efficiency of capital allocation between the agricultural sector and the nonagricultural sector. However, from the perspective of subdivided industries in the nonagricultural sector, the development of the digital economy may worsen the efficiency of factor allocation within the nonagricultural sector; on the one hand, it may trigger the flow of labor factors from the secondary industry to the tertiary industry, which, in turn, will aggravate the labor shortage in the secondary industry and promote the economy to "turn from real to virtual"; on the other hand, it may promote the flow of capital factors from the secondary industry to the tertiary industry, aggravate the shortage of capital input in the secondary industry and the excessive capital input in the tertiary industry, and then, worsen the factor allocation efficiency between the secondary industry and the tertiary industry. Therefore, on the basis of the factor allocation efficiency of the dual-economy sector studied in this paper, it is now necessary to go deeper into the nonagricultural sector to study the impact of the development of the digital economy on the factor allocation efficiency of the nonagricultural sector, which also constitutes an important research direction for the authors in the future.

The above research content examined the reasons and mechanisms behind the influence of the digital economy on the efficiency of factor allocation between sectors of the dual-economy from the perspective of the flow direction of production factors between sectors. Next, this paper further used the variables of sectoral factor input status (excessive or insufficient) calculated by the factor allocation efficiency evaluation model to empirically test whether the digital economy can truly promote the capital and labor factor input of the agricultural sector and the nonagricultural sector to close to the effective level. This paper distinguished the sample data into the excessive group and the insufficient group according to the input status of labor and capital factors in the agricultural and nonagricultural sectors and, then, continued to use the bidirectional fixed effect model for regression analysis.

It can be seen from Table 7 that the sample size of the excessive group of capital input in the agricultural sector is 0 because the status of capital input in the agricultural sector is seriously insufficient in the empirical data sample. It can be seen from the second column in the upper part of Table 7 that, when the capital factors of the agricultural sector are in a state of insufficient input, the development of the digital economy can significantly increase its capital factor input and, then, promote the capital factor input of the agricultural sector to move closer to the effective state. In terms of labor factors in the agricultural sector, when the input of labor factors in the agricultural sector is in a state of excessive input, the development of the digital economy can significantly reduce the input of labor factors in the agricultural sector and, then, promote the input of labor factors to the effective state. When the labor factors of the agricultural sector are insufficient, the effect of the development of the digital economy on the input status of its labor factors is positive, but not significant, that is, if the labor input of the agricultural sector is insufficient, then the development of the digital economy will not improve the efficiency of the allocation of labor factors by promoting labor employment in the agricultural sector. This is closely related to China's rapid urbanization process, where urban labor is unwilling to return to the agricultural and rural fields for related work. The research of Tian [7] showed that the digital economy can drive labor mobility from the agricultural sector to the nonagricultural sector, but he did not verify how the digital economy will guide the flow and allocation of capital elements between the agricultural and nonagricultural sectors. In addition, The research of Tian [7] did not further demonstrate whether labor mobility triggered by the digital economy can improve factor allocation efficiency. The above research conclusion of this article further proves, on the basis of the research of Tian [7], that the factor flow triggered by the development of the digital economy can effectively improve the efficiency of factor allocation between the agricultural and nonagricultural sectors, thereby enhancing the total factor productivity of the economy.

Table 7. The impact of the digital economy on factor input efficiency of the agricultural and nonagricultural sectors.

Model	Pk_1		Pl_1	
Explained Variable	$Pk_1 > 1$	$Pk_1 < 1$	$Pk_1 > 1$	$Pk_1 < 1$
digi	-	0.3200 *** (2.98)	−0.8378 *** (0.5259)	0.0705 (0.49)
Control variables	-	Yes	Yes	Yes
Time fixed effect	-	Yes	Yes	Yes
Individual fixed effect	-	Yes	Yes	Yes
Adjusted R^2	-	0.1866	0.5259	0.9429
Sample size	0	300	242	58
Model	Pk_{23}		Pl_{23}	
Explained Variable	$Pk_{23} > 1$	$Pk_{23} < 1$	$Pl_{23} > 1$	$Pl_{23} < 1$
digi	−0.3358 *** (−3.34)	-	0.0974 (0.70)	0.2991 ** (2.51)
Control variables	Yes	-	Yes	Yes
Time fixed effect	Yes	-	Yes	Yes
Adjusted R^2	0.4954	-	0.8288	0.5614
Sample size	300	0	58	242

Note: t-values are in parentheses; ***, ** represent signiffcance at the 1%, 5% levels, respectively.

In terms of factor input efficiency in the nonagricultural sector, since the capital factors of the nonagricultural sector are in a state of excess, the sample size of the capital factor input ratio of the nonagricultural sector less than 1 is 0. When the capital input state of the nonagricultural sector is in an excessive state, the development of the digital economy can significantly reduce its capital factor input and promote the capital factor input state to move closer to the effective state. Continuing to look at labor factors, when the labor factor input in the nonagricultural sector is in an excessive state, the development of the digital economy has a positive effect on its labor factor input, but it is not statistically significant. When the labor factor input of the nonagricultural sector is in a state of shortage and inadequacy, the development of the digital economy can significantly improve the input of labor factors, promote the labor factors to move closer to the effective state, and then, optimize the labor factor input efficiency of the nonagricultural sector.

In summary, through the above empirical analysis, the effect of digital economy development in promoting the flow of production factors between the agricultural and nonagricultural sectors has been further verified at the level of factor allocation efficiency, that is the process of digital economy development promoting the flow of labor factors from the agricultural sector to the nonagricultural sector and promoting the flow of capital factors from the nonagricultural sector to the agricultural sector by driving nonagricultural employment is an important internal influence mechanism for improving the efficiency of factor allocation between the dual-economy sectors.

6.2. The Impact of Factor Allocation Efficiency between the Dual-Economic Sectors on the Income Gap between Urban and Rural Areas

The above empirical analysis verified that the development of the digital economy can significantly improve the factor allocation efficiency between the dual-economy sectors, and then, this paper carried out the second empirical research, that is empirically examining whether the improvement of factor allocation efficiency between the dual-economy sectors can narrow the income gap between urban and rural areas.

A significant endogenous problem in this part of the empirical process is that there may be a two-way causal relationship between factor allocation efficiency between the dual-economy sectors and the urban–rural income gap, that is the change of the urban–rural income gap will also affect the factor allocation efficiency between the dual-economy sectors. In order to solve this endogeneity, this paper used the IV-2SLS method for regression analysis, and in the empirical process, the lagging for one period of the total factor misallocation, capital misallocation, and labor misallocation were selected as tool variables to avoid possible endogenous problems, then the IV-GMM method was used for robustness testing to effectively verify the reliability and robustness of the empirical research conclusions in this paper. The specific empirical results are shown in Table 8.

Table 8. The impact of the factor allocation efficiency of the binary economy on the income gap between urban and rural areas.

Explained Variable	***Gap***	***Gap***	***Gap***	***Gap***	***Gap***	***Gap***
Method	***IV-2SLS***	***IV-2SLS***	***IV-2SLS***	***IV-GMM***	***IV-GMM***	***IV-GMM***
Mis	0.9133 *** (4.68)			1.0282 *** (5.31)		
Musk		1.0064 *** (3.96)			1.1772 *** (4.56)	
Misl			7.4670 *** (4.90)			7.5158 *** (4.91)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.6835	0.6137	0.5162	0.6824	0.6197	0.5116
Sample size	270	270	270	270	270	270

Note: t-values are in parentheses; *** represent signiffcance at the 1% levels, respectively.

It can be seen from Table 8 that, when using the IV-2SLS method for regression analysis, provided that other conditions are equal, the total factor misallocation, capital misallocation, and labor misallocation between the dual-economy sectors are all positive and significant at the level of 1%, that is the increase in the level of factor misallocation between the sectors of the dual-economy can significantly widen the income gap between urban and rural areas. Among these, labor misallocation had the largest widening effect on the urban–rural income gap, followed by capital misallocation, and the widening effect of total misallocation was the smallest. The reason may be that the correction of the misallocation of labor factors between the dual-economy sectors not only optimizes the labor factor input efficiency of the agricultural sector, but also optimizes the labor factor input efficiency of the secondary industry and the tertiary industry within the nonagricultural sector, that is the marginal output of labor factors in the agricultural sector and the nonagricultural sector is Pareto-improved, which will help narrow the income gap between urban and rural areas. With the improvement of capital misallocation, on the one hand, the efficiency of capital input within the agricultural sector has been improved, but the capital misallocation between the secondary and tertiary industrial sectors within the nonagricultural sector may be aggravated by the reflow and reallocation of capital factors between the dual-economy sectors, which may lead to the further widening of the already narrowed urban–rural income gap and weaken the income distribution optimization effect brought about by the improvement of the capital factor allocation efficiency. After superimposing the impact of capital misallocation and labor misallocation on the urban and rural income distribution, the total misallocation had the smallest widening effect on the urban–rural income distribution gap, which can also be explained by the above logic.

Columns 4–6 of Table 8 show the results of the analysis using the IV-GMM method regression, which shows that the factor misallocation between the sectors of the binary economy can indeed widen the income gap between urban and rural areas, and its effect is highly consistent with the analysis results of the IV-2SLS method. This shows that the empirical analysis results of this paper have good robustness and persuasiveness.

Next, the internal influence mechanism between the digital economy, dual-economic factor allocation efficiency, and urban–rural income gap was verified through empirical analysis methods. Firstly, this paper set the dummy variable LO of the labor factor input state in the agricultural sector so that the sample of the labor factor input state in the agricultural sector in the excessive state is equal to 1; otherwise, it is 0. This paper then multiplied the digital economy development variable with the above dummy variable LO to form the cross-term jiaochal. The first column of Table 9 shows that the digital economy can significantly reduce the excessive level of labor factor input in the agricultural sector and improve the efficiency of labor factor input in the agricultural sector. The regression results in the second column of Table 9 show that the development of the digital economy can significantly reduce the income gap between urban and rural areas. The regression results in the third column of Table 9 show that the increase in the excessive level of labor factor input in the agricultural sector can significantly widen the income gap between urban and rural areas. In the fourth column of Table 9, this paper put the digital economy development level variable and the intersection term into the regression equation at the same time and analyzed the income gap between urban and rural areas. The regression results show that the crossover term variable was significantly negative at the 10% level, and the regression coefficient of the digital economy development level variable was positive and not significant after adding the multiplication term, which indicates that, if other conditions remain unchanged, digital economy development can indeed narrow the urban–rural income gap by reducing the excessive level of labor factor input in the agricultural sector.

We continued to see whether the digital economy can narrow the income gap between urban and rural areas by alleviating the shortage of capital input in the agricultural sector. Similarly, this paper first set up the virtual variable CU of insufficient capital factor input in the agricultural sector; when the capital factor input in the agricultural sector is insufficient, the virtual variable is 1; otherwise, it is 0. Then, the variable of the level of digital economy development is multiplied by the virtual variable of insufficient capital input in the agricultural sector to form the multiplication term jiaochak. The first column in the lower part of Table 9 shows that, all else being equal, an increase in the development of the digital economy can significantly alleviate the shortage of capital input in the agricultural sector. The second column of the empirical results shows that the digital economy can significantly reduce the income gap between urban and rural areas. The third column of the empirical regression results shows that the improvement of the capital factor input level in the agricultural sector can significantly reduce the urban–rural income gap, that is the agricultural sector with insufficient capital factor input can play a role in simultaneously reducing the urban–rural income gap in the process of improving the level of capital factor input. The fourth column of the empirical regression results puts in both the digital economy development level variable and the multiplier variable, and the regression results show that the regression coefficient of the multiplier variable was significantly negative at the level of 1%; after adding the multiplication term, the impact of the digital economy development level variable on the urban–rural income gap became insignificant, so it can be concluded that digital economy development can indeed alleviate the urban–rural income gap by increasing the capital factor input of the agricultural sector.

Table 9. The internal mechanism of the digital economy affecting the urban–rural income gap: the perspective of alleviating the excessive input of agricultural labor factors and the insufficient input of capital factors.

Explained Variable	***LO***	***Gap***	***Gap***	***Gap***
digi	−1.0422 ** (−2.51)	−0.2867 *** (−4.53)		0.2108 (1.20)
jiaochal				−0.2542 * (−1.83)
LO			0.1084 * (1.89)	
Control variables	YES	YES	YES	YES
Time effect	YES	YES	YES	YES
Adjusted R^2	0.2399	0.4534	0.7604	0.5353
Sample size	270	270	270	270
Explained Variable	**CU**	***Gap***	***Gap***	***Gap***
digi	0.3200 *** (2.98)	−0.2867 *** (−4.53)		0.0681 (1.17)
jiaochak				−0.3196 *** (−3.30)
CU			−0.0829 *** (−4.57)	
Control variables	YES	YES	YES	YES
Time effect	YES	YES	YES	YES
Adjusted R^2	0.2024	0.4534	0.6527	0.6754
Sample size	270	270	270	270

Note: t-values are in parentheses; ***, **, and * represent signiffcance at the 1%, 5%, and 10% levels, respectively.

7. Conclusions

The digital economy has significant economic structural transformation effects and income distribution effects. This paper analyzed the impacts and mechanisms of digital economy development on the allocation factor efficiency of the dual-economy and the urban–rural income gap from a theoretical level and used China's provincial panel data from 2008 to 2017 for empirical testing. The following was found: (1) There is a significant factor misallocation between China's dual-economy sectors. As of 2017, the average factor misallocation between the dual-economy sectors in China's provinces was as high as 24.22%, of which the average capital misallocation was 21.77% and the average labor misallocation was 4.01%, that is the factor misallocation between China's dual-economy sectors is mainly caused by capital misallocation. From the perspective of the factor input efficiency in the agricultural sector and the nonagricultural sector, the labor factors of the agricultural sector in most provinces and cities in China are in a state of over-input, while capital is in a state of insufficient input, and this state has not been significantly improved over time. Excessive investment of capital in the nonagricultural sector has led to a series of socio-economic problems, and the agricultural sector has always faced obstacles in technical reformation and transformation and upgrading due to a lack of capital input. Labor cannot flow smoothly and freely from the agricultural sector to the nonagricultural sector, resulting in a large amount of redundant labor force in the agricultural sector and an increasing shortage of labor in the nonagricultural sector. (2) Through empirical analysis, this paper found that the development of the digital economy significantly improves the factor allocation efficiency of the dual-economy in China and has a significant improvement effect on the factor allocation efficiency of capital and labor. (3) The factor misallocation of the dual-economy has significantly widened the income gap between urban and rural areas, and the impact of the labor factor misallocation on the urban–rural income gap was significantly greater than that of capital factor misallocation. (4) The analysis and development of the impact mechanism: the development of the digital economy alleviates the problem of excess labor factors and insufficient capital input in the agricultural sector by promoting nonagricultural employment and the flow of capital factors to the agricultural sector, thereby improving the efficiency of the factor allocation of the dual-economy; the development of the digital economy can significantly reduce the income gap between urban and rural areas by improving the factor allocation efficiency of capital and labor in the dual-economy.

The policy implications of this article include the following: Firstly, the development of the digital economy can promote nonagricultural employment, guide capital factors to invest in agriculture, and promote agricultural transformation and upgrading, as well as help narrow the urban–rural income gap. Therefore, it is necessary to vigorously develop the digital economy. Secondly, while the digital economy promotes the flow of labor from the agricultural sector to the nonagricultural sector, policies should pay more attention to guiding the reasonable flow of labor between the secondary and tertiary industries, in order to prevent the potential problem of "detachment from reality to emptiness" caused by the development of the digital economy.

The main contribution of this paper was to verify that the development of the digital economy can promote the rational flow and optimal allocation of production factors such as capital and labor between the agricultural and nonagricultural sectors through theoretical and empirical analysis, thereby narrowing the income gap between urban and rural areas in China and optimizing the income distribution pattern between urban and rural areas in China. This means that China is expected to make full use of the achievements of the third technological revolution represented by the digital economy to promote economic structural transformation and create a reasonable income distribution pattern.

The limitation of this article is that it only verified that the digital economy can promote the flow of labor from the agricultural sector to the nonagricultural sector, thereby improving the efficiency of factor allocation between the binary economic sectors and narrowing the urban–rural income gap. However, this article did not further explain whether the digital economy can promote an effective division of labor within the nonagricultural sector for mobile labor. This will constitute the authors' future research direction.

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