# A Study on Measuring the Efficiency of Digital Inclusive Finance Enabling High-Quality Fiscal Development in Provinces

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**Abstract.** With the rapid development of the global economy, digital inclusive finance as a new innovative model directly affects the real economy, which also has a boost for local government finance. In order to realize digital inclusive finance empowering local financial development, this paper takes 31 provinces' financial development as the research object, selects digital inclusive finance data and 31 provinces' panel data during 2015-2021, and applies DEA three-stage data envelopment analysis to construct the evaluation index system of the efficiency of each province's financial development based on the environmental indicators, which contains input indicators, output indicators and environmental variables and combines with the Malmquist index for dynamic analysis, found that South China has the highest efficiency after empowerment, while Northwest China has the lowest, at the same time, need to pay more attention to the environment in East China and North China, and the total factor productivity is affected by the epidemic in 2021 and the trade friction between China and the United States, showing a decreasing trend. Accordingly, this paper proposes to deepen the depth of the use of digital inclusive finance by strengthening the cooperation between relevant technology and financial companies and other suggestions to emphasize the development of digital inclusive finance, pay attention to the impact of environmental factors, and appropriately increase the scale of implementation and other countermeasures.

**Keywords:** Digital Inclusive Finance, DEA three-stage data envelopment analysis, Malmquist Index, Financial development.

## 1. Introduction

Based on the rapid development of the global economy, China's market economy is also constantly developing and progressing, and innovation has become a key factor for the survival and development of today's enterprises [1-2]. Especially for small and medium-sized enterprises, innovation can improve their core competitiveness to cope with market changes and challenges. As a new financing method, digital inclusive finance has brought new financing channels for small and medium-sized enterprises [3-4]. Small and medium-sized enterprises can better apply funds to innovation so that enterprises can constantly respond to changes in the environment. Digital inclusive finance will directly affect the development of enterprises' real economy, so the relationship between digital inclusive finance and real economy has been highly valued by the government and society. As the constituent cells of social workers, small and medium-sized enterprises contribute an important source of income to the development of local finance. Digital inclusive finance, a new financing method, ultimately benefits local finance through small and medium-sized enterprises. At present, due to the short implementation time of digital inclusive finance, the efficiency of digital inclusive finance for local finance is still unknown [5-6]. In order to explore the financial efficiency of

provinces with the negative impact of digital inclusive finance, this paper uses the DEA model to discuss the implementation effect of digital inclusive finance policy, and based on this, puts forward relevant suggestions to promote the development of digital inclusive finance in China.

## 2. Literature Review

### 2.1. Digital Financial Inclusion Efficiency Evaluation Methods

The methods of evaluating the efficiency of digital financial inclusion in China mainly include one-stage DEA, three-stage DEA, the Malmquist index method, etc. Sun Wuqin et al. used the DEA model to measure the efficiency of financial development in promoting technological innovation in 23 provinces and cities in China, and found that the role of financial development in technological innovation and technological output efficiency was becoming more and more obvious, and showed a gradually strengthening trend, but did not study the influencing factors. Zeng Jianghong and Chen Diyu et al. (2008)[7] selected 37 SMEs and conducted an empirical analysis of the financing efficiency of SMEs by using a one-stage DEA model from the perspective of financing usage and financing cost,but ignored the influence of random errors ; Zeng Yanbing[2] used BCC, SBM combination model to evaluate the technical efficiency of Xiamen senior citizens' institutional services and analyzed the influencing factors through Tobit regression model. analyzing the influencing factors, etc. Established studies refine the environmental factors and other influencing factors of the sample, but their effects are not effectively separated, while the effects of some random factors fail to appear. The three-stage DEA can make up for the shortcomings of the above methods that cannot eliminate the effects of random factors and external environmental factors on efficiency. Considering that the three-stage DEA model is only from the static point of view, which can only reflect the static efficiency situation in the same period, ignoring the impact of time changes, this paper innovatively combines the three-stage DEA model with the Malmquist model to make up for the missing dynamic efficiency changes due to time changes. Based on the above empirical analysis, this paper takes digital finance as the input, finance as the output, and considers the influence of environmental factors, applies the three-stage DEA model, and adopts the panel data of China's 31 provinces from 2015 to 2021 to conduct a comprehensive analysis of the urban unemployment rate, urban-rural income gap, and gross domestic product due to finance; at the same time, the results of the analysis are compared and contrasted with those of the first and third stages respectively; at the same time, based on the first and third stages, the results of the analysis are compared and contrasted. At the same time, according to the results of the first and third stages of analysis, the first-stage DEA is easy to ignore the impact of environmental variables, which leads to large errors and limitations in the measured efficiency values, while the efficiency values measured by the three-stage DEA method can more objectively reflect the target regional disparities, and combined with the Malmquist model, reflect the dynamic efficiency changes over multiple periods of time. Therefore, this study adopts the combination of three-stage DEA and Malmquist model to measure the efficiency of digital financial inclusion in 31 provinces in China.

### 2.2. Indicator system construction

The project studies the impact of digital inclusive finance on local financial revenue, and in the establishment of the indicator system, it is divided into two parts: input and output. Among them, the input part mainly refers to the development level of digital inclusive finance in China. For the study of the development level of local digital finance, the Digital Inclusive Finance Research Center of Peking University and Ant Financial Group have jointly compiled the 2011-2018 " Digital Inclusive Finance Index" covering 31 provinces, 337 cities above prefecture level, and about 2,800 counties by building a comprehensive index system and using hundreds of millions of microdata in China through the use of big data and cloud computing technologies. Peking University Digital Financial Inclusion Index" [9], in which the index includes three dimensions, i.e., breadth of coverage, depth of use and degree of digital support services. The output component mainly refers to China's fiscal revenue,

which the project team divided into three parts: fiscal revenue, fiscal expenditure, and deficit rate. Among them, fiscal revenue refers to the monetary income obtained by the government in a certain period of time. Drawing on the practice of Song Baolin et al. (2022)[10], this paper adopts the general fiscal revenues of local governments to measure local fiscal revenues. Fiscal expenditure is the process of allocating and utilizing fiscal revenues, and fiscal expenditure includes the sum of government expenditures at all levels. Considering the unification of indicators, this paper also adopts the general fiscal expenditure of local governments as the counterpart of fiscal expenditure. Deficit ratio is an important indicator of fiscal risk, referring to the proportion of fiscal deficit to GDP.

## 3. Research Methods

The Data Envelopment Analysis (DEA) is a non-parametric method combined with linear programming, proposed by Charnes et al. in 1978, used to evaluate multiple-input and multiple-output decision-making units of the same type. The DEA method effectively simplifies the calculation steps and has more prominent advantages compared to traditional statistical methods, thus finding widespread applications in various fields. However, the conventional DEA models cannot eliminate the interference of external factors such as environmental factors. In this paper, a three-stage DEA model is employed, which combines the traditional DEA model with Stochastic Frontier Analysis (SFA) to remove the external interference of environmental factors from the initial DEA results and then conduct a second round of DEA estimation. Through the three-stage estimation process, the accuracy of the model is significantly improved, aiming to obtain the true efficiency of each decision-making unit as much as possible.

First stage: Constructing the initial DEA model. In this study, the Variable Returns to Scale (VRS) BCC model is chosen. After collecting the data and using the DEAP 2.1 software to input the input and output indicators of the decision-making units into the traditional DEA model, the original efficiency values and the slack variables to be invested are obtained.

Second stage: Estimating the impact of environmental variables on the technical efficiency values of each decision-making unit, conducting slack variable analysis, and adjusting input values using the SFA model to ensure that all study subjects are assessed for efficiency under the same environmental conditions. The calculation formula is as follows:

$$\widehat{Q_{ab}} = Q_{ab} + [\max(Z_b, \beta^a) - Z_b\beta^a] + [\max(V_{ab}) - V_{ab}] \quad (1)$$

$\widehat{Q_{ab}}$ represents the adjusted input values, while $Q_{ab}$ represents the initial input values before adjustment. $[\max(Z_b, \beta^a) - Z_b\beta^a]$ represents the adjustment based on the worst environmental value as a standard for adjusting other environmental factors. $[\max(V_{ab}) - V_{ab}]$ represents the unification of the random luck levels of all the study subjects. To perform the adjustment, Frontier 4.1 software is utilized. The input variables obtained in the first stage, along with the environmental variables, are set as explanatory variables and dependent variables, respectively. Through the calculation process, the adjusted input values are obtained, which eliminate the influence of random factors and external interferences such as environmental variables.

Third stage: It is necessary to recompute the efficiency values of the decision-making units (DMUs). The overall computation method remains the same, but the adjusted input values $\widehat{Q_{ab}}$ are used instead of the original input values $Q_{ab}$ DEAP 2.1 software is employed to input the adjusted values into the traditional DEA model to calculate the efficiency. As a result, the true efficiency of each decision-making unit, after eliminating external interference factors, is obtained.

## 4. Data sources and selection of indicators

### 4.1. Data Source

This study takes the financial development of 31 provinces (excluding Hong Kong, Macao and Taiwan) in China as the research object, and selects the cross-section data of digital financial coverage

breadth, depth of digital financial use, degree of digital services, digital innovation R&D expenses, fiscal revenues, fiscal expenditures, deficit rate, unemployment rate, urban-rural income disparity, and industrial structure of the 31 provinces during the period of 2015-2021 as the data for the study. The main data come from China Statistical Yearbook and Peking University Digital Inclusive Finance Index.

### 4.2. Selection of Indicators

#### 4.2.1 Selection of Input/Output Variables

In order to evaluate the efficiency of high-quality financial development in each province, this paper selects the provincial fiscal revenue, fiscal expenditure and deficit rate as output indicators; at the same time, in order to more accurately study the impact of digital financial empowerment, this paper selects the breadth of digital financial coverage in the 31 provinces, the depth of digital financial use, the degree of digitalization services, and digital innovation R&D expenses as digital financial input indicators; with the development of technology and the continuous change of the 5G era, digital finance needs to match the catching up with the digital financial index. changes, digital finance needs to match the ability to catch up with the technological frontier of the times in order to comply with the trend of technological development of the times and lead the construction of financial development of the provinces, therefore, this paper adds digital innovation R&D expenses as the indicator of technological innovation ability on the basis of the breadth of coverage, depth of use, and degree of digitalization service of the original issue of the Peking University Digital Financial Inclusion Index of Peking University (see Table 1), which is a more sound way to improve the indicator structure for measuring the efficiency of financial development in digitally empowered provinces.

**Table 1.** Description of input-output indicators for the evaluation of fiscal efficiency in the provinces

| Category | Dimension | Specific indicators | Serial number |
|---|---|---|---|
| Digitization inputs | Breadth of Coverage | Breadth of digital financial coverage | X1 |
| | Depth of use | Depth of use of digital amounts | X2 |
| | Degree of digitization | Degree of digitalization of financial inclusion | X3 |
| | Technological innovation ability | Digital innovation R&D expenses | X4 |
| Development outputs | Fiscal Development | Financial Revenue | Y1 |
| | | Fiscal Expenditure | Y2 |
| | Fiscal risk | Deficit rate | Y3 |

#### 4.2.2 Selection of environmental variables

Environmental variables are factors that can have an impact on the efficiency of high-quality development of finance in each province, but the decision-making unit cannot control itself, so its impact on the measurement of the efficiency of high-quality development of finance in each province needs to be eliminated in the process of measurement. Referring to the research on the efficiency of other related industries or fields, and combining the development characteristics of the economic environment of each province, the three environmental variables as shown in Table 2 are selected.

**Table 2.** Selection of environmental variables for fiscal efficiency in each province

| Variable Type | Indicators | Specific variables | Serial number |
|---|---|---|---|
| Environment Variables | Level of social employment | Unemployment rate | Z1 |
| | Level of wealth gap | Fiscal Revenue Gap | Z2 |
| | Level of industrial structure | Industrial structure | Z3 |

China's statistical yearbook has not yet soundly covered the indicators directly reflecting the level of employment, so this paper selects the unemployment rate of each province to reflect the level of social employment side by side. This paper uses the ratio of the difference between disposable income per capita of urban residents and disposable income per capita of rural residents to the ratio of disposable income per capita of rural residents as the fiscal revenue gap to measure the extent of the gap between the rich and the poor in each province, while the industrial structure of each province also has a far-reaching impact on the fiscal revenue of each province, so we use the value added of the secondary industry plus the total value added of the tertiary industry and the proportion of the regional GDP to reflect the industrial structure.

## 5. Analysis of empirical results

### 5.1. The first stage: analysis of traditional DEA model results

According to the traditional DEA model, DEAP2.1 software is applied to measure the efficiency of digital inclusive finance in 31 provinces of China, and the results are shown in Table 3.

**Table 3.** Digital financial inclusion efficiency of 31 provinces in China from 2015 to 2021 in the first phase

| Efficiency value range (region) | Average of combined efficiency | Mean value of pure technical efficiency | Average scale efficiency |
|---|---|---|---|
| Central China | 0.835 | 0.974 | 0.854 |
| Southwest China | 0.86 | 0.988 | 0.859 |
| Northwest China | 0.626 | 0.986 | 0.636 |
| Northeast China | 0.699 | 0.976 | 0.717 |
| East China | 0.801 | 0.943 | 0.831 |
| North China | 0.808 | 0.965 | 0.832 |
| South China | 0.91 | 0.987 | 0.92 |

It can be seen that the comprehensive efficiency of South China is higher and that of Northwest China is lower among the 7 regions in China. In terms of pure technical efficiency, the southwest region has higher pure technical efficiency, while the East China region has lower pure technical efficiency. In terms of scale efficiency, the scale efficiency in South China is higher, while the comprehensive efficiency in Northwest China is lower. It can be concluded that in terms of comprehensive efficiency and scale efficiency, the implementation effect of digital inclusive finance in South China has a significant result compared with other regions, so it can bring better development of local finance in South China. In terms of pure technical efficiency, the southwest region has a higher pure technical efficiency, so it can be concluded that the pure technical efficiency level of digital inclusive financial efficiency is better implemented in the southwest region.

### 5.2. The second stage: SFA-based stochastic frontier analysis

**Table 4.** Summary of SFA model regression results

| parameters | Breadth of coverage | Depth of use | Degree of digitisation | Technological innovativeness |
|---|---|---|---|---|
| **Constant term** | -76.45 | -73.31 | -10.48 | -3429759.50 |
| **Unemployment rate** | 2.46 | -2.80 | -0.12 | -500609.38 |
| **Fiscal revenue gap** | 2.59 | 0.72 | -2.05 | -513101.72 |
| **Industrial structure** | 65.00 | 80.24 | 13.92 | 5299838.10 |
| $\sigma^2$ | 397.81 | 826.48 | 184.12 | 3568025000000.00 |
| $\gamma$ | 1.00 | 1.00 | 1.00 | 1.00 |

The second stage utilizes the SFA-like regression model with the input slack variables obtained in the first stage as the explanatory variables. The external environment variables such as unemployment rate, fiscal income gap, and industrial structure are used as explanatory variables. The like SFA regression analysis was conducted using Frontier 4.1 software and analyzed the cross-sectional data from 2015-2021. The regression results are shown in Table 4: (The regression results for the year 2021 are selected to be presented in this paper)

#### 5.2.1 Social employment level

The regression coefficients of social employment level with the slack variables of depth of use, degree of digitization technological innovation capacity are significantly negative, and the regression coefficients with the breadth of coverage slack variable are significantly positive, when the social employment level changes, when the unemployment rate rises, the market downturn, and the demand for loans for micro, small, and medium-sized enterprises (MSMEs) increases, which leads to an increase in the redundancy of the breadth of the coverage of the digital inclusive finance. However, the redundancy of depth of use, the redundancy of digitization and the redundancy of innovation capacity of the technology branch may be limited due to the higher financing needs of the unemployed population and the instability of credit status, thus showing a negative correlation with the unemployment rate.

#### 5.2.2 Urban-rural income gap

An increase in the urban-rural income gap is positively correlated with the breadth of coverage and depth of use of digital finance, and an increase in the urban-rural income gap implies that rural areas have relatively lower income levels and lag behind in economic development. Redundancy in breadth of coverage and depth of use means that digital inclusive financial services are able to cover a wider range of areas and more customers, and are able to meet their financing needs more accurately. Thus, an increase in the urban-rural income gap reflects higher demand for loans in rural areas, which drives an increase in redundancy in the breadth of coverage and redundancy in the depth of use of digital financial inclusion. In contrast, the negative correlation between the increase in the urban-rural income gap and the redundancy in digitization and the redundancy in technological innovation capacity is a result of the fact that rural areas are relatively lagging behind in terms of economic development, and may have lower penetration of digital financial services, in addition to the fact that infrastructure and technical support in rural areas may be relatively weak, which limits the extent of digitization and technological innovation capacity. Therefore, the increase of urban-rural income gap will lead to the reduction of digitization degree and redundancy of technological innovation capacity.

### 5.2.3 Industrial structure

The regression coefficients of the slack variables of industrial structure and the coverage breadth, use depth, digitization degree and technological innovation capacity of digital finance are significantly positive. The upgrading of industrial structure means that more enterprises and individuals develop in the service industry, which often requires more financial support and will increase the financing demand of the service industry, thus covering the increase in the breadth of redundancy. At the same time, the upgrading of the industrial structure will bring more enterprises in the service sector, and different enterprises and industries may have different financing needs and risk characteristics, which will increase the diversity and specificity of the service sector, thus prompting loan service providers to provide more precise financing services and contributing to the increase in the use of depth redundancy. The upgrading of industrial structure will prompt more enterprises and individuals to participate in the service industry, and their requirements for the convenience and efficiency of loan services will also increase, which will prompt loan service providers to continuously improve the convenience of their services to meet the growing demand for financing in the service industry, prompting an increase in the degree of redundancy in digitization. And industrial structural upgrades are often accompanied by advances in technology and innovation. These technological advances will increase the efficiency and accuracy of the lending process, thus driving an increase in the redundancy of technological innovation capabilities. For example, through the application of technologies such as artificial intelligence, big data analytics and blockchain, loan service providers are able to assess risks and approve loan applications more quickly and accurately, thereby improving the efficiency of loan services and causing an increase in redundancy in technological innovation capacity.

## 5.3. The third Stage:Analysis of DEA model results after removing environmental variables

Through the use of DEAP 2.1 software, a re-measurement of the input and output values for the eight major regions after removing environmental variables was conducted. The results from this stage are then compiled together with the results from the first stage, as shown in Table 1.

According to Table 3, after removing environmental factors, the average values of comprehensive technical efficiency, pure technical efficiency, and scale efficiency for the eight major regions from 2015 to 2021 have undergone changes. Among them, the comprehensive technical efficiency of the eight major regions has only decreased by 0.04%, pure technical efficiency has increased by only 0.082%, and scale efficiency has decreased by 0.05%. Among these indicators, the largest change is observed in pure technical efficiency. However, overall, the changes in all three indicators are relatively small. This indicates that environmental factors have little impact on the influence of technological innovation on fiscal revenue.

Regarding comprehensive technical efficiency, after removing environmental factors, only the South China region has a comprehensive technical efficiency greater than 0.9, indicating that it is close to the production frontier. Other regions should strive to achieve the production level of South China. Central China, Northwest China, and East China have seen an increase in technical efficiency after eliminating environmental factors, suggesting that these regions are still affected by negative environmental influences and need to pay attention to environmental factors. Furthermore, only the Northwest and Northeast regions have comprehensive technical efficiency below 0.8, indicating that these two regions have relatively weak development in digital finance. The influence of digital finance on regional fiscal revenue is also relatively weak, indicating that there is still significant room for improvement in these areas.

Regarding pure technical efficiency, after removing environmental factors, the Southwest region maintains its pure technical efficiency at the frontier level without any change. All regions have pure technical efficiency above 0.9, and the differences between them are relatively small. This indicates that high-tech enterprises generally have high levels of pure technical utilization. Among them, the East China and North China regions show a significant improvement compared to other regions after

removing environmental factors, suggesting that these two regions still need to pay greater attention to environmental factors.

Regarding scale efficiency, after removing environmental factors, only the South China region has a scale efficiency above 0.9. The Central China, East China, and North China regions are all above 0.8, while the Southwest and Northwest regions are below 0.7, indicating relatively lower scale efficiency in these two regions.

### 5.4. Efficiency analysis based on the Malmquist index

**Table 5.** Malmquist index and its decomposition indicators of the efficiency of digital finance on finances in each province, 2013-2021

| YEAR | EFFCH | TECHCH | PECH | SECH | TFPCH |
|---|---|---|---|---|---|
| 2015-2016 | 1.043 | 0.966 | 1.002 | 1.041 | 1.007 |
| 2016-2017 | 0.962 | 0.93 | 1.004 | 0.958 | 0.895 |
| 2017-2018 | 0.981 | 0.904 | 0.985 | 0.996 | 0.887 |
| 2018-2019 | 1.055 | 0.867 | 1.018 | 1.036 | 0.915 |
| 2019-2020 | 0.988 | 1.021 | 1.007 | 0.981 | 1.009 |
| 2020-2021 | 0.935 | 0.691 | 0.982 | 0.952 | 0.646 |

Due to the different production frontiers selected for the three-stage DEA analysis, the results are static and the trend of efficiency changes cannot be observed by comparing the changes from year to year. Therefore, this paper calculates the Malmquist index and its decomposition index for the years 2015-2021 to overcome this limitation. The results are shown in Table 5.

According to the technological progress change index (TECHCH) of each province's finance in Table 5, the technological progress of each province's finance in China in the 4G era (2015-2019) has shown a gradual downward trend, and the index has been less than 1, which indicates that the technological level of each province in China's domestic provinces has been in a state of technological stagnation during the period of 2015-2019. In 2019, the technological progress change index reached its maximum value, which may be closely related to the arrival of the 5G era.2019 is the era of 5G entering commercialization, which marks the official arrival of the 5G era.The technological revolution and progress brought about by 5G has greatly improved the popularization and promotion of digital financial inclusion in all provinces, which has made the technological progress change index reach its peak in 2019. In contrast, the technological progress change index plummeted from 1.021 to 0.691 between 2020-2021, which is related to the malicious sanctions imposed on China's technology giant Huawei Co. by the U.S. side. Huawei is one of the first companies in the world to research 5G technology, 5G technology to bring social science and technology technological progress of the changes in the United States attention, in its Huawei company during the 2020 years to take various malicious sanctions, China's 5G technology has a certain impact, may be due to the reason caused by China's provinces, technological progress change slightly stagnant.

Scale efficiency change index (SECH) and pure technical efficiency change index (PECH) of the change in the magnitude of the smaller and the two show the same trend of change, the trend is stable to good. As both the scale efficiency change index (SECH) and the pure technical efficiency change index (PECH) are steadily improving, the technical efficiency change index (EFFCH) also shows a steady increasing trend. Meanwhile, due to the impact of the epidemic aspect, during the epidemic period (2020-2021), the provinces face many financial challenges. At the beginning of the epidemic, the provinces' finances were reduced in size, and the pure technical efficiency of the provinces' finances decreased significantly, by 95.2% compared to 2019. This indicates that the epidemic had a significant impact on the operations of the provincial treasuries. This may be due to the local policy reduction in revenue caused by the VAT credit rebate, with the developed eastern provinces experiencing a greater corresponding reduction in revenue due to the large size of their manufacturing industries and other enterprises eligible for the rebate.

The Scale Efficiency Change Index (SECH), Pure Technical Efficiency Change Index (PECH), and Technical Efficiency Change Index (EFFCH) gradually increase in 2015-2020, but due to the national hand epidemic and the trade friction between China and the U.S. in 2021, it causes significant fluctuations in the Technological Advancement Change Index (TECHCH) in 2021, resulting in a significant fluctuation in the Total Factor Productivity ( TFPCH) shows a decreasing result in 2021 after a stable increase in 2015-2020.

## 6. Conclusions and Suggestions

Through three-stage DEA analysis and Malmquist index analysis, this paper conducted dynamic and static analysis on the efficiency of local financial development empowered by digital inclusive finance in 31 provinces in China from 2015 to 2021 and drew the following conclusions:

(1)Static analysis shows that after removing environmental factors, the average values of comprehensive technical efficiency, pure technical efficiency, and scale efficiency of digital inclusive finance in China have all changed. From 2015 to 2021, the values of comprehensive technical efficiency and scale efficiency have decreased, while the values of pure technical efficiency have increased. Compared with other regions, environmental factors have a greater impact on the implementation efficiency of digital financial inclusion policies in East and North China, indicating that these two regions still need to pay more attention to environmental factors. In addition, the returns to scale in most provinces are increasing, and production efficiency should be improved by expanding production scale.

(2)Dynamic analysis: Before the epidemic, the pure technical efficiency of 31 provinces in China increased under the promotion of digital inclusive finance policy. From 2015 to 2020, digital inclusive finance in all regions enhanced the overall efficiency of local financial development, but in 2021, the social progress index decreased due to the epidemic and Sino-US trade friction. Total factor productivity declines.

Based on the presented situation, the following suggestions are proposed in this article:

(1)Emphasize the development of inclusive digital finance: As digital technologies continue to emerge, inclusive digital finance has been instrumental in promoting fiscal development in various regions. Therefore, local governments should prioritize the development of inclusive digital finance. This can be achieved by focusing on four aspects to improve the utilization of inclusive digital finance: increasing digital infrastructure and providing relevant knowledge training to expand its coverage; strengthening collaboration between technology and financial companies to deepen its usage; innovating digital technologies and introducing advanced platforms to enhance its digitalization; attracting tech-savvy talent and implementing innovation incentives to improve technological capabilities.

(2)Implement appropriate scale of inclusive digital finance: Based on the increasing returns to scale, regions should appropriately expand the scale of implementing inclusive digital finance to increase scale benefits and allocate resources effectively, thereby improving resource utilization.

(3)Pay attention to the impact of environmental factors in each region: To enhance fiscal revenue, regions should consider various factors such as regional value-added, taxation, unemployment rate, and imports/exports. By controlling environmental factors and identifying the optimal input combination, regions can achieve synergy between increased utilization and expanded scale of inclusive digital finance, ultimately improving comprehensive technical efficiency.

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