

Research Article

Prediction of High-Tech Talents Flow Impact on Labor Income Share: Based on DEA and Fractional Hausdorff Grey Model

Wei Cui , Anwei Wan , and Yongbo Yang 

Faculty of Finance and Economics, Jiangsu University, Zhenjiang, Jiangsu 212013, China

Correspondence should be addressed to Anwei Wan; 1044258119@qq.com

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The purpose of this paper is to analyze the impact of high-tech talents flow on labor income share and explore the influencing mechanism. It can be proved that high-tech talents flow affects labor income share by production function, with technological progress as a mediator variable. The labor income share is the dependent variable, and the gravity of high-tech talents as the independent variable is the index to measure the high-tech talents flow, constructing the panel data model with the Malmquist index of technological progress as a mediator variable. Furthermore, the Malmquist index of technological progress is decomposed into catching-up of technological progress index and leapfrogging of technological progress index, which, respectively, replaces the Malmquist index of technological progress as a mediator variable in the panel data model. Regression analysis shows that technological progress is a mediator variable for high-tech talents flow to reduce labor income share, and the impact mainly comes from leapfrogging of technological progress. However, although the mediating effect of catching-up technological progress index is not significant at the significance level of 10%, it is a mediator variable for high-tech labor mobility to increase income share at the significance level of 20%. Finally, this paper predicts the change in labor income share from 2018 to 2027 by the fractional Hausdorff grey model, and the results show that it is an increasing trend. However, the Gini coefficient whose change trend is opposite to the labor income share remains high in the past two years, indicating that there are other factors affecting the income gap, such as the urbanization rate and the transportation convenience. The innovation of this paper is mainly to reveal that the leapfrogging of technological progress is the major cause of the high-tech talents flow rising income inequality gap, while the catching-up of technological progress is the source of the former narrowing the latter. The fractional Hausdorff grey model predicts that the key determinants of income inequality gap are more than labor income share.

1. Introduction

China's carbon emissions are among the top in the world, so it has great pressure and potential to reduce carbon emissions. One of the best ways to reduce carbon emissions is technological progress [1]. Technological progress requires the introduction of high-tech talents, which may lead to two outcomes. Firstly, the introduction of high-tech talents improves the level of automation and increases machine input and energy consumption, but increases carbon emissions. So carbon reduction equipment is needed in order to reduce carbon emissions from machines. Thus, there is a need for more labor to operate, maintain, and repair these carbon emissions to reduce devices, where labor and capital are in complementary relationship. Therefore,

total labor income of the whole society increases in order to manage carbon emission from capital expansion; that is, labor income share may increase [2, 3]. Secondly, the increase in the employment of labor force due to carbon emission reduction also means an increase in production costs, a corresponding increase in commodity prices, and a decrease in demand, which leads to a decrease in demand for labor force, so the possibility of a decrease in labor income share is enhanced [2, 4].

Accordingly, the impact of the introduction of high-tech talents on the labor income share is uncertain on account of carbon emission reduction technological progress. However, changes in the labor income share significantly affecting the equality of income distribution are obvious. If the labor income share is low, social wealth tends to be allocated to

capital owners. Also, it may widen the gap between rich and poor to increase social instability [5]. If the labor income share is too high, it will lead to inflation [6]. The wage income of labor will be devalued, which not only reduces their quality of life but also hinders economic development. Therefore, labor income share should be kept within a reasonable range. Since technological progress is an important mediator variable for the introduction of high-tech talents to change labor income share, the law of technological progress deeply analyzed may be the key to mining the impact of high-tech talents flow on labor income share.

If technological progress is taken as a mediator variable, the reason for the uncertainty of the impact of the high-tech talents flow on the labor income share may be related to the mode of technological progress. Technological progress is divided into two modes [7], namely, catching-up and leapfrogging [8]. Technological progress was slow in the early stage of the emergence of new technologies. With the continuous promotion and popularization of technology, the progress speed was accelerating until natural limits or physical limits. At this time, the technology reached the mature stage, and the technological progress also encountered bottlenecks. It requires longer time and more resources to breaking through this bottleneck to achieve the leapfrogging of technological progress. The catching-up of technological progress is mainly technology promotion, which is manifested in the popularization of new machinery and equipment or the promotion of new production process. The leapfrogging of technological progress is mainly the replacement of old and new technologies, which is manifested as the emergence of new production tools. Therefore, the path of technological progress presents an S-curve trend [9]. Although the high-tech talents flow has an impact on the technological progress of the two models, the mechanism of technological change is different, and the role of the catching-up of technological progress is to improve production efficiency. By comparison, the role of the leapfrogging of technological progress is to produce new technologies. Consequently, the impact of high-tech talents flow on labor income share may be different due to different types of technological progress. On deep analysis, this impact may be the key to formulating income distribution policies and revealing the specific path of technological progress affecting labor income share.

The innovation of this paper is that the mediator variable of high-tech talents flow affecting labor income share is mainly the leapfrogging of technological progress rather than the catching-up of technological progress. Furthermore, the leapfrogging of technological progress is a mediator variable for high-tech talents flow to reduce labor income share at a significance level of 10%. Also, the catching-up of technological progress is a mediator variable for high-tech talents flow to increase labor income share at a significance level of 20%. Moreover, the impact of high-tech talents flow on labor income share is constrained by carbon emission reduction regulations. Fractional Hausdorff grey model predicts that the key determinants of income inequality gap are more than labor income share.

The rest of the article is arranged as follows. Section 2 is literature review. Section 3 is mechanism analysis. Section 4 is model construction. Section 5 is empirical analysis. Section 6 is conclusion.

2. Literature Review

2.1. Labor Mobility Affects Labor Income Share. The more skilled the labor, the greater the labor income share in developed countries; the more skilled the labor, the smaller the labor income share in developing countries [10]. This is related to differences in industrial efficiency and elasticity of substitution among products among countries. Differences in industrial efficiency lead to differences in product prices, triggering the labor flow. If substitution elasticity between products is greater than 1, labor flows from low-technology to high-technology sectors. If the elasticity of substitution between products is less than 1, the result of labor flows is opposite [11]. High-tech industries in developed countries are more efficient and match highly skilled labor, so the more the labor, the greater the labor income share. However, developing countries are completely opposite [12]. Therefore, the technical level is related to labor mobility and its labor income share. Panel data from 11 industrialized countries show that both technological advances in the industrial sector prior to the Second World War and subsequent technological advances in the agricultural sector are drivers of labor mobility [13]. Similar conclusions were obtained by the industrial evolution model and counterfactual analysis with data from 45 countries from 1970 to 2005. This may be because technological progress has changed productivity across sectors and has led to trans-sectoral labor mobility [14]; for example, the industrial structure of the United States changed from industry to service with the flow of labor and the corresponding change in the labor income share in various industries from 1960 to 2005 [15]. Thus, technological progress is an important mediator between labor mobility and labor income share.

2.2. Impact of Technological Progress on Labor Income Share. The impact of technological progress on the share of labor income is uncertain. Zeira [16] constructed an automated economic growth model. This model showed that the higher the proportion of automation input, the higher the proportion of capital output. Based on this study, Aghion et al. [17] analyzed the impact of technological progress on income share in terms of automation and Baumol's disease. On the one hand, automation inputs increase returns on capital and capital income share, while they decrease labor income share, that is, substitution effects [18, 19]. On the other hand, the labor income share increased because of Baumol's disease, that is, countervailing effect [20, 21].

Technological progress can lead to higher unemployment while improving labor productivity, that is, substitution effect [22, 23]. So 47% of jobs in the US, 59% in Germany, and 1.7% in Canada are replaced by machines with technological advances [24, 25]. The reason for the large difference in substitution rates among the three countries

may be because the statistical calibers are inconsistent. After unification, the values of the three countries become 9%, 12%, and 9%, respectively [26].

In fact, however, employment in countries of the twentieth century has maintained a trend of growth [27], which suggests that technological progress can also increase jobs [28] and therefore has a countervailing effect. Although scientific and technological progress has led to a greater substitution effect than complementary effects for industrial machines to labor in the United States, adding one machine will reduce employment by 0.18–0.34 percent [18], but this result is related to the nature of the industry. The textile, steel, and automotive industries are substitution effects in the US, while the nonmanufacturing industry is the complementary effect, and the increase in mechanization has increased employment between capital and labor [29]. Similar phenomena exist in Germany. The promotion of machines reduces manufacturing employment but increases employment in services [30]. The increase in employment means that the labor income share may increase.

Income distribution inequality is generally increased whether scientific and technological progress increases or decreases the labor income share. Even though low-skilled and high-skilled labor may be replaced by machines in technological progress, the former increases income inequality and the latter reduces income inequality [31]. However, capital returns are higher because machines are replicable [32]. Furthermore, machine costs fall led to labor income share fall as technology matures [33]. Therefore, income inequality shows an increasing trend.

A considerable number of environmental technology innovation results have been produced in response to global environmental protection pressure. At present, environmental regulation is an important constraint for technological innovation, and its impact on labor income share has also become the focus of academic circles.

2.3. Impact of Environmental Regulation on Labor Income Share. Environmental regulation has a significant effect on labor income share [34]. Environmental protection policy and labor employment may be negative correlation. Developed countries began to attach importance to environmental protection and introduced stricter environmental protection systems, which led to an increase in unemployment in the 1970s [35]. A survey shows that one-third of interviewee feedback that their work is threatened by environmental regulation in 1990 [2], but there are also scholars who argue that these interviewees are overstated because they ignore environmental regulation also creates jobs [36]. Therefore, the direct impact of environmental regulation on employment is still unclear [37].

On the one hand, environmental regulation increases marginal costs, which results in lower output and reducing labor demand. Greenstone (2002) analyzed the impact of the Clean Air Act Amendments on the labor demand of the industrial sector and found that the labor force in counties that failed to meet the air emission

requirements of the Act Amendments decreased by 590000 people from 1972 to 1987 in order to meet the air emission standards in the United States. Similar cases occurred in Spain. In 1990, this country amended the Clean Air Act. Walker [38] estimated a 15 percent decline in labor force in the industrial sector in counties not meeting the standard to counties meeting the standard. Therefore, the introduction of new environmental protection bills or amendments to environmental protection regulations may lead to reduced labor demand and increased unemployment [3, 37, 39].

On the other hand, environmental regulation may also increase the employment rate. More workers are needed to install, operate, and repair new machines because of new technologies. Numerous studies have shown that this phenomenon is widespread. For example, the United States SCAQMD Act and CAFÉ standards created 300,000 jobs [4, 40]. Although these policies aim to reduce carbon emissions and improve energy efficiency, they also create more jobs [41].

Thus, the correlation between environmental regulation and labor income share is also uncertain. Britain's carbon tax policy has not significantly changed manufacturing employment rate [42], but British Columbia's carbon tax police has significantly increased employment [43]. However, this result was denied by Chi [44], and he found that the policy led to an increase of 1.3% in unemployment.

Existing studies have shown that high-tech labor mobility accelerates technological innovation spillover, which may change the labor income share. However, there are three points that need further analysis. Firstly, although the flow of high-tech labor force can change the labor income share, it is not clear whether it is caused by catching-up of technological progress or leapfrogging of technological progress, which leads to the failure to correctly guide the flow of talents to improve labor income share. Secondly, there is opposite correlation among technological progress, environmental regulation, and labor income share in different literature studies, but there is no literature systematically discussing the reasons, which makes it impossible to find incentive measures for scientific and technological progress to effectively improve labor income share under different environmental regulations. Thirdly, the literature of the impact of labor mobility on labor income share ignores the mediator variable of technological progress, leading to the lack of an effective method of technological innovation path improving labor income share.

In view of this, this paper introduces the Malmquist index of carbon emission reduction technological progress and uses the IDA (Index Decomposition Analysis) to decompose it into catching-up of technological progress index and the leapfrogging of technological progress index. This paper analyzes the influence of the high-tech labor flow on the labor income share with these two kinds of technological progress indexes as mediator variables and then gives the possible path to increase the labor income share. Also, fractional Hausdorff grey model is used to predict the change in labor income share to forecast the fairness of income distribution.

2.4. Mechanism Analysis of High-Tech Talents Flow Affecting Labor Income Share. An aggregate production function, $F(L, M, A)$, includes two inputs, which are L and M . A is a technology index in $F(L, M, A)$. And L is unskilled workman, while M could be capital, skilled labor, or land according to Acemoglu [45]. But skilled labor should not belong to M but to L according to the definition of labor. So L and M are high-tech talent and capital, respectively, in the $F(L, M, A)$.

Without loss of generality, imagine that $\partial F/\partial A > 0$; the more the introduction of talents are, the greater the level A is, the better the technology is. Introducing the talents could improve technology from two aspects, which is, respectively, the leapfrogging and the catching-up.

Technical change is the leapfrogging if the production function takes the more special form $F(AL, M)$. Also, technical change is the catching-up if the production function takes the more special form $F(L, AM)$. $F(AL, M)$ means labor efficiency improvement breaks through old technologies to realize the leapfrogging of technological progress because of more and more knowledgeable, capable, and intelligent workers in the employment market. However, $F(L, AM)$ means the capital efficiency improvement may be caused by new machines usage or new technical skill extension which is the catching-up of technological progress.

Technical change is L-biased, which means increment of labor income share, if

$$\frac{\partial(\partial F/\partial L)/(\partial F/\partial M)}{\partial A} > 0, \quad (1)$$

that is, technical change increases the marginal product of high-tech talent more than M .

The constant elasticity of substitution (CES) production function is calculated in equation (2), and the relative marginal product of L and M is calculated in equation (3). For more details on the properties of production function and marginal function, refer to [45]:

$$y = [\gamma(A_L L)^{(\sigma-1/\sigma)} + (1-\gamma)(A_M M)^{(\sigma-1/\sigma)}]^{(\sigma/\sigma-1)}, \quad (2)$$

$$\frac{MP_M}{MP_L} = \frac{1-\gamma}{\gamma} \left(\frac{A_M}{A_L}\right)^{(\sigma-1/\sigma)} \left(\frac{M}{L}\right)^{-1/\sigma}, \quad (3)$$

with A_M (capital efficiency) and A_L (labor efficiency) calculated in equations (4) and (5) based on Box-Cox transformations according to Bencik, M. [46]:

$$A_M = M_0 e^{g_M(t)}, \quad (4)$$

$$A_L = L_0 e^{g_L(t)}, \quad (5)$$

in which $g_M(t)$ and $g_L(t)$ are the contribution of capital efficiency and labor efficiency, respectively.

Then, equations (4) and (5) replace A_M and A_L in equation (3), respectively. And the result is shown in the following equation:

$$Q = \frac{MP_M}{MP_L} = \frac{1-\gamma}{\gamma} \left(\frac{A_M}{A_L}\right)^{(\sigma-1/\sigma)} \left(\frac{M}{L}\right)^{-1/\sigma}. \quad (6)$$

Technical change is the leapfrogging of technological progress or the catching-up of technological progress, which is decided by technical bias. Also, the technical bias could be calculated by time derivative of equation (6). The result is shown as follows:

$$\frac{dQ}{dt} = \frac{1-r}{r} \left(\frac{M_0}{L_0}\right)^{(\sigma-1/\sigma)} \left(\frac{M}{L}\right)^{-1/\sigma} \left(\frac{\sigma-1}{\sigma}\right) \left[\frac{e^{g_M(t)}}{e^{g_L(t)}} \right]^{-1/\sigma} \frac{e^{g_M(t)} \cdot e^{g_L(t)} [g'_M(t) - g'_L(t)]}{[e^{g_L(t)}]^2}. \quad (7)$$

If $\sigma < 1$, high-tech talents and capital are complementary effects with increasing returns to scale. Also, new technology replaces old technology, which is the leapfrogging of technological progress, so the marginal contribution of labor efficiency is more than capital efficiency [47] because new technological breakthrough relies on high-tech talents, that is, as shown in equation (8). However, $\sigma < 1$ means that more capital needs to be put on production. Hence, $dQ/dt > 0$ in equation (7). This means the technical bias is capital bias. In other words, the leapfrogging of technological progress would increase capital income share and decrease high-tech talent income share. Moreover, the unskilled labor efficiency is lower than the high-tech talent efficiency, so the unskilled labor income share also decreases when the high-tech talent income share decreases. Consequently, the leapfrogging of technological progress, which means increasing returns to scale, could decrease labor income share:

$$g'_M(t) < g'_L(t). \quad (8)$$

If $\sigma > 1$, it means the substitution effect between high-tech talent and capital with constant returns to scale. Also, the new technology is promoting after the leapfrogging of technological progress, such as the application of new machines and new process. Therefore, the marginal contribution of capital efficiency is more than labor efficiency [8], so the technical change is capital-biased, that is, equation (9). Also, $dQ/dt > 0$ in equation (7), but the technical bias would change equation (9) into equation (10) because of the law of diminishing marginal returns and $dQ/dt < 0$. If $dQ/dt > 0$, the catching-up of technological progress would decrease high-tech talent income share. If $dQ/dt < 0$, the catching-up of technological progress would increase high-tech talent income share, so the catching-up of technological progress may increase or decrease the labor income share because high-tech talent is part of labor:

$$g'_M(t) > g'_L(t), \tag{9}$$

$$g'_M(t) < g'_L(t). \tag{10}$$

Thus, because of high-tech talents flow, the leapfrogging of technological progress decreases the labor income share, while the catching-up of technological progress ambiguously impacts on labor income share.

3. Malmquist Index with DEA, Panel Model, and Fractional Hausdorff Grey Model

3.1. *Malmquist Index and Decomposition Analysis Based on DEA.* Technological progress as a mediator variable can be measured by Malmquist index [48]. Färe et al. [49] developed it as a nonparametric method described by Shephard distance function. The advantage of this method is that it is easy to determine the optimal solution to improve

technological progress, and the disadvantage is that it is unable to solve the measurement model of technological progress with CO₂ constraints. Thus, it is necessary to combine the static environmental performance measurement method by Tyteca [50] to define the distance function of CO₂ as in equation (11). K , L , and E are input capital, labor, and energy. Y and C are output GDP and CO₂. The δ value indicates the maximum promotion of technological progress under the pressure of carbon emission reduction. On this basis, Malmquist index MQI can be constructed. Malmquist index can be based on both t -period technology and $(t + 1)$ period, so the geometric average of the Malmquist index in these two periods is used to measure the technological progress under the constraint of carbon emission reduction from t -period to $(t + 1)$ period in order to avoid different measurement results due to different periods, as shown in formula (12):

$$D(K, L, E, Y, C) = \sup\{\delta: (K, L, E, Y, C/\delta) \in P(K, L, E)\}, \tag{11}$$

$$MQI(t, t + 1) = \frac{D^t(K^t, L^t, E^t, Y^t, C^t) \cdot D^{t+1}(K^t, L^t, E^t, Y^t, C^t)}{D^t(K^{t+1}, L^{t+1}, E^{t+1}, Y^{t+1}, C^{t+1})D^{t+1}(K^{t+1}, L^{t+1}, E^{t+1}, Y^{t+1}, C^{t+1})}, \tag{12}$$

where $(K^t, L^t, E^t, Y^t, C^t)$ and $(K^{t+1}, L^{t+1}, E^{t+1}, Y^{t+1}, C^{t+1})$ are t -period and $(t + 1)$ period of input-output, respectively; D^t and D^{t+1} , respectively, represent the distance function of technological progress in period t and $(t + 1)$. Solving the method of distance function is environmental DEA model

[51]. Hence, the Malmquist index of technological progress of carbon emission reduction is based on four periods of technology, so four distance functions are solved, as shown in formula (13), where p and q represent periods and $p, q \in (t, t + 1)$:

$$\begin{aligned} \min \delta &= [D^p(K^q, L^q, E^q, Y^q, C^q)]^{-1} \\ \text{s.t. } \sum_{i=1}^I \lambda_i K_i^p &\leq K_i^q, \sum_{i=1}^I \lambda_i L_i^p \leq L_i^q, \sum_{i=1}^I \lambda_i E_i^p \leq E_i^q, \sum_{i=1}^I \lambda_i Y_i^p \geq Y_i^q, \sum_{i=1}^I \lambda_i C_i^p = \delta C_i^q, \quad \lambda_i \geq 0, i = 1, 2, \dots, I. \end{aligned} \tag{13}$$

Malmquist index of carbon emission reduction technological progress can be further decomposed into catching-up index (CCI) and leapfrogging index (LFI), that is, $MQI = CCI \cdot LFI$, as shown in (14) and (15), respectively. Also, $MQI > 1$ represents carbon emission reduction

technological advances. $CCI > 1$ and $LFI > 1$ mean that the catching-up of technological progress and the leapfrogging of technological progress are the reasons for carbon emission reduction technological progress, respectively. Also, the meaning of $MQI < 1, CCI < 1$, and $LFI < 1$ is opposite:

$$CCI(t, t + 1) = \frac{D^t(K^{t+1}, L^{t+1}, E^{t+1}, Y^{t+1}, C^{t+1}) \cdot D^t(K^t, L^t, E^t, Y^t, C^t)}{D^{t+1}(K^t, L^t, E^t, Y^t, C^t)D^{t+1}(K^{t+1}, L^{t+1}, E^{t+1}, Y^{t+1}, C^{t+1})}, \tag{14}$$

$$LFI(t, t + 1) = \frac{D^{t+1}(K^{t+1}, L^{t+1}, E^{t+1}, Y^{t+1}, C^{t+1})}{D^t(K^t, L^t, E^t, Y^t, C^t)}. \tag{15}$$

3.2. Panel Model. According to the mechanism analysis, a panel data model is used to analyze the impact of high-tech talents on labor income share. According to a study by Grunewald et al. [52], the dependent variable is labor income share (LSrate); the core independent variable is the labor gravitation (Labor_grav). The mediator variable is carbon emission reduction technology (CERT). Furthermore, the control variables include the level of urbanization (Urb), education level (Edu) [53], basic pension insurance (Pen) [54], unemployment insurance (Unempl) [55], health insurance (Heal) [56], highway density (Hwd), and railway density (Rwd) [57]. All control variables are referred to the research by Wei [58] and represented by γ_{ij} . The specific models are as follows:

$$\text{LSrate}_{it} = \lambda_0 + \lambda_1 \text{Labor_grav}_{it} + \sum \lambda_{it} \cdot \gamma_{it} + u_{it}, \quad (16)$$

$$\text{CERT}_{it} = \tau_0 + \tau_1 \text{Labor_grav}_{it} + \sum \tau_{it} \cdot \gamma_{it} + \varepsilon_{it}, \quad (17)$$

$$\text{LSrate}_{it} = \beta_0 + \beta_1 \text{Labor_grav}_{it} + \beta_2 \text{CERT}_{it} + \sum \beta_{it} \cdot \gamma_{it} + \xi_{it}. \quad (18)$$

It divides into three steps to judge the mediating effect. The first step is to check whether the labor gravitation has a significant impact on the labor income share, as shown in equation (14). If it is significant, then the second step is to test whether the labor gravitation significantly affects the carbon emission reduction technology, as shown in equation (15). If it is significant, then the third step is to examine the significance of the impact of labor gravitation and carbon emission reduction technology on the labor income share. If the impact of labor gravitation is significant, the carbon emission reduction technology is the mediator variable of the labor gravitation impacting the labor income share.

3.3. Fractional Hausdorff Grey Model. The data for this article are from 2007 to 2017 because of some unpublished data, so it is necessary for the prediction model to predict the change in labor income share in the future. Because of the small amount of data in this paper, grey theory may be suitable for building the prediction model. At present, the prediction accuracy of fractional Hausdorff grey model (FHGM) is higher than that of other models, which is suitable for the prediction analysis in this paper. For the specific form of FHGM, this study refers to the research of Meng et al. and Shi and Wu [59, 60].

$$\hat{x}^{(0)}(k+1) = \frac{(1 - e^{-\hat{a}})(x^{(0)}(1) - \hat{b}/\hat{a})e^{-\hat{a}k}}{(k+1)^r - k^r}, \quad (k = 1, 2, \dots, n). \quad (19)$$

4. Index, Data, and Results

4.1. Index Selection, Data Sources, and Descriptive Statistics. This paper studies the impact of high-tech talents flow on labor income share based on the carbon emission reduction technology as the mediator variable in China. The variable

Labor_grav is the labor gravitation measured by gravitation in the high tech workforce, and its calculation method refers to the research of Witt & Witt (1995) [61]. The mediator variable CERT is carbon emission reduction efficiency based on environmental DEA methodology measuring carbon emission reduction technology. The control variables include Urb measured by the proportion of urban population in each province; Edu is measured by the average education years using the concrete calculation method of $(6 + \text{Edu})/28$ because most Chinese citizens begin attending elementary school at the age of 6 and graduate with a doctoral degree at the age of 28; Pen, Unempl, and Heal are pension, unemployment insurance, and health insurance, respectively, measured by the ratio of each type of insurance participant to the total population in each province; Hwd and Rwd are, respectively, measured by the ratio of highway and railway mileage to the total population in each province [58].

The data selection, data sources, and data calculation methods are as follows. The data pertaining to population, capital, labor, and GDP are also from the China Statistical Yearbook. The perpetual inventory method is used to calculate capital, taking 2000 as the basic period. Similarly, we calculate the actual GDP taking 2000 as the basic period. The data regarding energy consumption come from the China Energy Statistical Yearbook. CO₂ data are from the “Energy” section in the “2006 IPCC Guidelines for National Greenhouse Gas Inventories” designated by the Intergovernmental Panel on Climate Change, which can be specifically calculated using the final consumption of industrial energy data from the China Energy Statistical Yearbook. The Urb, Edu, Pen, Unempl, and Heal data are all from the China Urban Statistical Yearbook. The data regarding highway and railway mileage are from the China Transportation Statistical Yearbook. In the absence of data from individual indices in some provinces, we use a balanced data set with annual measurements from 2007 to 2017, covering 25 provinces. The summary statistics of these data are shown in Table 1.

4.2. Results

4.2.1. Results of Malmquist Index. The carbon emission reduction efficiency measuring as Malmquist index of 25 provinces is calculated in China using formulas (12) and (13), as shown in Table 2. It can decompose into the catching-up and the leapfrogging of technological progress using formulas (14), (15), and (13), as shown in Tables 3 and 4, respectively.

4.2.2. Results of Panel Data Model. Malmquist index of carbon emission reduction technology is used as a mediator variable to verify the impact of high-tech talents flow on labor income share. High-tech talents flow reduces labor income share at a significance level of 5% according to formula (16) and model 1 in Table 5. Then, according to formula (17), high-tech talents flow promotes technological progress in carbon emission reduction at a significance level of 5% according to model 2 in Table 5. Also, at a significance

TABLE 1: Summary statistics for our balanced panel set.

Variable	Unit	Mean	SD	Min	Max
<i>Main variables</i>					
<i>G</i>	Percentage scale	0.378	0.050	0.251	0.490
δ	Percentage scale	0.636	0.264	0.124	1.000
<i>Mediator variables</i>					
<i>Labor_grav</i>	Percentage scale	0.004	0.006	4.361E-05	0.033
<i>Controls</i>					
<i>Urb</i>	Percentage scale	0.528	0.136	0.275	0.896
<i>Edu</i>	Percentage scale	0.544	0.049	0.449	0.732
<i>Pen</i>	Percentage scale	0.402	0.214	0.051	0.811
<i>Unempl</i>	Percentage scale	0.119	0.084	0.035	0.513
<i>Heal</i>	Percentage scale	0.358	0.226	0.059	1.093
<i>Hwd</i>	Kilometer/hundred person	0.366	0.228	0.057	1.384
<i>Rwd</i>	Kilometer/thousand person	0.102	0.092	0.017	0.497

Data source: calculation. Total number of observations is 275.

TABLE 2: Calculation results of Malmquist index of carbon emission reduction technology of 25 provinces.

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hebei	0.2840	0.2645	0.2476	0.2314	0.2010	0.1666	0.1743	0.1431	0.1412	0.1233	0.1146
Liaoning	0.1852	0.1694	0.1581	0.1359	0.1453	0.1206	0.1237	0.1073	0.1035	0.0948	0.0842
Shanghai	0.2074	0.1822	0.1685	0.1564	0.1553	0.1119	0.1167	0.1240	0.1172	0.1043	0.0981
Jiangsu	0.3533	0.3200	0.3313	0.2954	0.2761	0.2512	0.2635	0.2318	0.2254	0.2053	0.1449
Zhejiang	0.8659	0.4150	0.3903	0.3333	0.3249	0.2601	0.2623	0.2577	0.2301	0.1976	0.1762
Fujian	1.0000	0.7574	1.0000	1.0000	1.0000	1.0000	1.0000	0.4726	0.4919	0.4741	0.4711
Guangdong	0.6185	0.6034	0.5831	0.5742	0.5243	0.4164	0.4246	0.3648	0.3586	0.3417	0.3183
Hainan	0.7009	0.6355	0.6114	0.5829	0.6022	0.5157	0.4977	0.4676	0.4589	0.4322	0.4253
Shanxi	0.4249	0.3764	0.3442	0.3230	0.3394	0.2657	0.2784	0.2389	0.2369	0.2273	0.2151
Heilongjiang	0.7007	0.6160	0.5712	0.5357	0.5538	0.4150	0.4530	0.4425	0.4298	0.4397	0.4746
Anhui	0.5827	0.5054	0.5032	0.4438	0.4821	0.3972	0.4418	0.3278	0.3214	0.2980	0.2865
Jiangxi	0.4209	0.3613	0.3510	0.3221	0.3042	0.2540	0.2775	0.2722	0.2665	0.2662	0.2573
Henan	0.4129	0.3917	0.3970	0.3782	0.3332	0.2488	0.2803	0.3333	0.3367	0.3385	0.3298
Hubei	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Inner Mongolia	0.5355	0.4898	0.4714	0.4176	0.3963	0.3210	0.3302	0.3128	0.3098	0.3211	0.2952
Guangxi	0.7791	0.6714	0.5717	0.5318	0.5836	0.4174	0.4343	0.4035	0.3961	0.3687	0.3998
Sichuan	0.5419	0.5057	0.4022	0.3986	0.4415	0.3321	0.3507	0.4164	0.3837	0.3922	0.3949
Chongqing	0.5957	0.4973	0.4516	0.4041	0.3968	0.3557	0.3518	0.3379	0.3440	0.3513	0.3593
Guizhou	0.1620	0.1551	0.1716	0.1547	0.1609	0.1289	0.1306	0.1382	0.1504	0.1592	0.1488
Shaanxi	0.4854	0.3937	0.3700	0.3541	0.3300	0.2656	0.2603	0.2655	0.2577	0.2424	0.2356
Gansu	0.3034	0.2744	0.2468	0.2496	0.2071	0.1720	0.1700	0.1609	0.1601	0.1492	0.1483
Qinghai	0.3096	0.2985	0.2595	0.2370	0.2707	0.2108	0.1954	0.1850	0.1813	0.1613	0.1367
Ningxia	0.1453	0.1314	0.1322	0.1221	0.1182	0.0722	0.0796	0.0763	0.0735	0.0660	0.0663
Xinjiang	0.3158	0.2832	0.2528	0.2025	0.2151	0.1577	0.1385	0.1159	0.1032	0.0908	0.0775

Data source: calculation.

level of 10 percent, high-tech talents flow reduces the labor income share through technological advances in carbon emission reduction according to formula (18) and model 3, as shown in Table 5.

It is noteworthy that carbon emission reduction technology has a full mediating effect. Then, it can be proved that the real mediating variable is leapfrogging rather than catching-up of technological progress, as

shown in Tables 6 and 7. In model 4, high-tech talents flow promotes leapfrogging of technological progress at a significance level of 10% in Table 6. Also, leapfrogging of carbon emission reduction technological progress as a mediator variable reduces labor income share with high-tech talents flow in model 5 in Table 6. If catching-up of technological progress is taken as the mediator variable, high-tech talents are introduced to enhance catching-up

TABLE 3: Calculation results of the catching-up index of carbon emission reduction technology of 25 provinces.

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	0.9446	0.9457	0.9524	0.9658	0.8997	0.9548	0.9556	0.9556	0.9214	0.9569	0.9446
Hebei	1.0263	1.0266	1.0365	1.2359	1.4518	0.8332	1.3260	0.9366	1.1145	1.0602	1.0263
Liaoning	1.0724	1.0425	1.2363	0.8162	1.4020	0.8307	1.1872	0.9811	1.0120	1.1599	1.0724
Shanghai	1.1533	1.0561	1.0575	0.9455	1.8105	0.8391	0.7910	1.0219	1.0714	1.0344	1.1533
Jiangsu	1.0954	0.8462	1.1477	1.0494	1.2848	0.8284	1.1547	0.9651	1.0231	1.8397	1.0954
Zhejiang	3.9718	1.0373	1.2618	0.9638	1.6673	0.8959	0.9256	1.1459	1.1502	1.1526	3.9718
Fujian	1.3510	0.6361	0.8955	0.9148	1.0991	0.8334	2.8946	0.8428	0.9319	0.9271	1.3510
Guangdong	0.9489	0.9769	0.9536	1.1109	1.7218	0.8514	1.2096	0.9449	0.9354	1.0549	0.9489
Hainan	1.0866	0.9768	1.0040	0.8610	1.5238	0.8919	1.0119	0.9482	0.9572	0.9454	1.0866
Shanxi	1.1439	1.0853	1.0432	0.8373	1.7721	0.8303	1.2128	0.9287	0.9227	1.0225	1.1439
Heilongjiang	1.1570	1.0495	1.0294	0.8728	1.8425	0.7653	0.9361	0.9677	0.8112	0.7858	1.1570
Anhui	1.1848	0.9097	1.1665	0.7849	1.5672	0.7369	1.6225	0.9496	0.9881	0.9901	1.1848
Jiangxi	1.2237	0.9598	1.0798	1.0459	1.3491	0.7635	0.9284	0.9527	0.8512	0.9799	1.2237
Henan	0.9951	0.8830	1.0078	1.1832	1.9368	0.7182	0.6317	0.8950	0.8401	0.9646	0.9951
Hubei	0.9782	0.9519	0.9612	0.9858	1.1457	0.9099	0.9538	0.9148	0.9099	0.9929	0.9782
Inner Mongolia	1.0685	0.9725	1.1531	1.0356	1.4335	0.8619	0.9953	0.9309	0.7904	1.0830	1.0685
Guangxi	1.2016	1.2232	1.0483	0.7745	1.8389	0.8419	1.0350	0.9473	0.9803	0.7784	1.2016
Sichuan	1.0237	1.4018	0.9239	0.7602	1.8070	0.8177	0.6335	1.0754	0.8125	0.9031	1.0237
Chongqing	1.2734	1.0912	1.1330	0.9675	1.3034	0.9318	0.9681	0.8812	0.8137	0.8754	1.2734
Guizhou	0.9740	0.7245	1.1168	0.8621	1.4658	0.8872	0.7985	0.7707	0.7578	1.0482	0.9740
Shaanxi	1.3562	1.0042	0.9906	1.0737	1.4602	0.9488	0.8585	0.9689	0.9596	0.9696	1.3562
Gansu	1.0873	1.0969	0.8864	1.3545	1.3644	0.9326	0.9972	0.9231	0.9777	0.9258	1.0873
Qinghai	0.9594	1.1734	1.0877	0.7152	1.5505	1.0609	0.9969	0.9489	1.0723	1.2762	0.9594
Ningxia	1.0923	0.8763	1.0631	0.9953	2.5201	0.7490	0.9739	0.9827	1.0514	0.9085	1.0923
Xinjiang	1.1100	1.1129	1.4142	0.8259	1.7506	1.1823	1.2763	1.1507	1.0958	1.2594	1.1100

Data source: calculation.

TABLE 4: Calculation results of the leapfrogging index of carbon emission reduction technology of 25 provinces.

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	0.9446	0.9457	0.9524	0.9658	0.8997	0.9548	0.9556	0.9556	0.9214	0.9569	0.9446
Hebei	1.0263	1.0266	1.0365	1.2359	1.4518	0.8332	1.3260	0.9366	1.1145	1.0602	1.0263
Liaoning	1.0724	1.0425	1.2363	0.8162	1.4020	0.8307	1.1872	0.9811	1.0120	1.1599	1.0724
Shanghai	1.1533	1.0561	1.0575	0.9455	1.8105	0.8391	0.7910	1.0219	1.0714	1.0344	1.1533
Jiangsu	1.0954	0.8462	1.1477	1.0494	1.2848	0.8284	1.1547	0.9651	1.0231	1.8397	1.0954
Zhejiang	3.9718	1.0373	1.2618	0.9638	1.6673	0.8959	0.9256	1.1459	1.1502	1.1526	3.9718
Fujian	1.3510	0.6361	0.8955	0.9148	1.0991	0.8334	2.8946	0.8428	0.9319	0.9271	1.3510
Guangdong	0.9489	0.9769	0.9536	1.1109	1.7218	0.8514	1.2096	0.9449	0.9354	1.0549	0.9489
Hainan	1.0866	0.9768	1.0040	0.8610	1.5238	0.8919	1.0119	0.9482	0.9572	0.9454	1.0866
Shanxi	1.1439	1.0853	1.0432	0.8373	1.7721	0.8303	1.2128	0.9287	0.9227	1.0225	1.1439
Heilongjiang	1.1570	1.0495	1.0294	0.8728	1.8425	0.7653	0.9361	0.9677	0.8112	0.7858	1.1570
Anhui	1.1848	0.9097	1.1665	0.7849	1.5672	0.7369	1.6225	0.9496	0.9881	0.9901	1.1848
Jiangxi	1.2237	0.9598	1.0798	1.0459	1.3491	0.7635	0.9284	0.9527	0.8512	0.9799	1.2237
Henan	0.9951	0.8830	1.0078	1.1832	1.9368	0.7182	0.6317	0.8950	0.8401	0.9646	0.9951
Hubei	0.9782	0.9519	0.9612	0.9858	1.1457	0.9099	0.9538	0.9148	0.9099	0.9929	0.9782
Inner Mongolia	1.0685	0.9725	1.1531	1.0356	1.4335	0.8619	0.9953	0.9309	0.7904	1.0830	1.0685
Guangxi	1.2016	1.2232	1.0483	0.7745	1.8389	0.8419	1.0350	0.9473	0.9803	0.7784	1.2016
Sichuan	1.0237	1.4018	0.9239	0.7602	1.8070	0.8177	0.6335	1.0754	0.8125	0.9031	1.0237
Chongqing	1.2734	1.0912	1.1330	0.9675	1.3034	0.9318	0.9681	0.8812	0.8137	0.8754	1.2734
Guizhou	0.9740	0.7245	1.1168	0.8621	1.4658	0.8872	0.7985	0.7707	0.7578	1.0482	0.9740
Shaanxi	1.3562	1.0042	0.9906	1.0737	1.4602	0.9488	0.8585	0.9689	0.9596	0.9696	1.3562
Gansu	1.0873	1.0969	0.8864	1.3545	1.3644	0.9326	0.9972	0.9231	0.9777	0.9258	1.0873
Qinghai	0.9594	1.1734	1.0877	0.7152	1.5505	1.0609	0.9969	0.9489	1.0723	1.2762	0.9594
Ningxia	1.0923	0.8763	1.0631	0.9953	2.5201	0.7490	0.9739	0.9827	1.0514	0.9085	1.0923
Xinjiang	1.1100	1.1129	1.4142	0.8259	1.7506	1.1823	1.2763	1.1507	1.0958	1.2594	1.1100

Data source: calculation.

TABLE 5: The estimation results of 25 provinces and Malmquist index is the mediator variable.

Variable	Model 1	Model 2	Model 3
Labor_grav	-1.82E-06**	33.7047**	-8.97E-07
δ	—	—	-6.45E-09*
Urb	-7.20E-08	-1.7256***	7.13E-08**
Edu	-1.43E-07*	-0.8861***	-1.48E-08
Pen	-1.68E-08	0.3854***	-1.05E-08
Unempl	3.41E-07***	-0.2192	-2.81E-08
Heal	-4.54E-08***	-0.0621	5.11E-09
Hwd	1.41E-07***	-0.3283	-1.35E-07***
Rwd	5.91E-08	0.3233	2.86E-08
β_0	1.01E-07**	2.2256***	8.60E-08***

*Significance under level of 10%; **significance under level of 5%; ***significance under level of 1%. Data source: calculation.

TABLE 6: The estimation results of 25 provinces and the leapfrogging index is the mediator variable.

Variable	Model 1	Model 4	Model 5
Labor_grav	-1.82E-06**	45.6037*	-9.99E-07*
δ	—	—	-2.25E-09*
Urb	-7.20E-08	-3.2636**	7.41E-08**
Edu	-1.43E-07*	-1.7484***	-1.35E-08
Pen	-1.68E-08	0.7745***	-1.10E-08*
Unempl	3.41E-07***	-0.5750	-2.81E-08
Heal	-4.54E-08***	-0.1777	5.06E-09
Hwd	1.41E-07***	-0.9849	-1.36E-07***
Rwd	5.91E-08	1.1321	2.94E-08
β_0	1.01E-07**	3.6416***	8.09E-08***

*Significance under level of 10%; **significance under level of 5%; ***significance under level of 1%. Data source: calculation.

TABLE 7: The estimation results of 25 provinces and the catching-up index is the mediator variable.

Variable	Model 1	Model 6	Model 7
Labor_grav	-1.82E-06**	15.63299*	-4.75E-07
δ	—	—	7.47E-09
Urb	-7.20E-08	-0.0463	-5.91E-08**
Edu	-1.43E-07*	-0.4683	5.88E-08
Pen	-1.68E-08	0.1568	2.66E-08
Unempl	3.41E-07***	-0.1812	-5.97E-08**
Heal	-4.54E-08***	-0.0101	4.61E-09
Hwd	1.41E-07***	0.0710	-1.12E-07***
Rwd	5.91E-08	-0.1601	1.84E-08
β_0	1.01E-07**	0.4337**	8.60E-08***

*Significance under level of 10%; **significance under level of 5%; ***significance under level of 1%. Data source: calculation.

of technological progress at the significance level of 10% in model 6, but catching-up of technological progress as a mediator variable has no significant effect on the change in labor income share in model 7. Therefore, leapfrogging of carbon emission reduction technological progress is a factor by which high-tech talents reduce labor income share.

4.2.3. *Labor Income Share Forecast Based on Fractional Hausdorff Grey Model.* Fractional Hausdorff grey model is used to predict the labor income share from 2018 to 2027, as shown in Table 8. Table 8 shows an increasing trend of labor income share in 25 provinces, indicating a clear and sustainable tendency in leapfrogging of technological progress over the next 10 years.

TABLE 8: Forecast of labor income share in 25 provinces by fractional Hausdorff grey model (unit: 10^{-8}).

	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Beijing	4.913	5.011	5.161	5.368	5.261	5.524	5.579	5.133	5.594	5.650
Hebei	4.922	5.020	5.171	5.270	5.378	5.534	5.589	5.142	5.605	5.661
Liaoning	1.773	1.809	1.863	1.938	1.994	1.899	2.014	1.853	2.019	2.040
Shanghai	4.237	4.322	4.452	4.630	4.537	4.764	4.811	4.873	4.427	4.825
Jiangsu	3.343	3.410	3.512	3.653	3.580	3.759	3.796	3.492	3.807	3.845
Zhejiang	2.593	2.724	2.644	2.833	2.915	2.776	2.944	2.709	2.952	2.982
Fujian	3.844	3.921	4.038	4.200	4.116	4.322	4.377	4.016	4.365	4.421
Guangdong	3.476	3.546	3.652	3.798	3.722	3.908	3.947	3.632	3.958	3.998
Hainan	4.454	4.543	4.679	4.867	4.769	5.008	5.058	4.653	5.072	5.123
Shanxi	0.960	0.979	1.008	1.048	1.027	1.079	1.090	1.002	1.093	1.104
Heilongjiang	1.609	1.641	1.690	1.758	1.723	1.809	1.827	1.681	1.832	1.850
Anhui	2.500	2.550	2.626	2.731	2.676	2.810	2.838	2.611	2.846	2.875
Jiangxi	2.216	2.261	2.329	2.422	2.373	2.492	2.517	2.316	2.524	2.549
Henan	3.118	3.180	3.276	3.541	3.339	3.506	3.407	3.257	3.550	3.586
Hubei	0.952	0.971	1.000	1.040	1.019	1.070	1.081	0.995	1.084	1.095
Inner Mongolia	1.257	1.282	1.321	1.314	1.346	1.414	1.428	1.374	1.432	1.446
Guangxi	1.890	1.927	1.985	2.065	2.023	2.124	2.146	1.974	2.152	2.173
Sichuan	1.901	1.939	1.998	2.077	2.036	2.138	2.159	1.986	2.165	2.187
Chongqing	0.928	0.946	0.975	1.014	0.993	1.043	1.054	0.969	1.057	1.067
Guizhou	3.236	3.300	3.399	3.535	3.465	3.638	3.674	3.380	3.685	3.721
Shaanxi	15.551	15.862	16.338	16.991	16.652	17.484	17.659	16.246	17.708	17.886
Gansu	3.808	3.884	4.000	4.160	4.077	4.281	4.324	3.978	4.336	4.379
Qinghai	1.995	2.035	2.096	2.180	2.136	2.243	2.266	2.084	2.272	2.295
Ningxia	5.761	5.876	6.053	6.295	6.169	6.477	6.542	6.019	6.560	6.626
Xinjiang	4.147	4.229	4.356	4.531	4.440	4.662	4.709	4.332	4.722	4.769

Data source: calculation.

5. Conclusions and Discussion

Based on the marginal substitution theory, if it is a leapfrogging of technological progress, then there is an increasing return to scale, and there is a complementary relationship between capital and labor; that is, capital income share increases, while labor income share decreases. If the catching-up of technological advances is made possible, production efficiency improves, capital income share increases, while labor income share decreases in the initial stage due to the popularization and application of new equipment. However, the marginal output decreases, and the carbon emissions are close to or exceed the delimitation with the continuous input of machinery and equipment. The relationship between capital and labor becomes substitution, and labor replaces capital, so the share of labor income increases. However, the marginal output decreases with the continuous input of machinery and equipment, and carbon emissions are close to or exceed the emission standard. The relationship between capital and labor becomes substitution relationship, and labor replaces capital, so the labor income shares increase.

The results can be proved by relevant data of 25 provinces in China. The introduction of high-tech talents significantly reduces labor income share by using Malmquist index as a mediator variable. If the Malmquist index is decomposed into the leapfrogging of technological progress index and the catching-up technological progress index, the former as a mediator variable is the reason for the introduction of high-tech talents to reduce the labor income

share, and the latter is not significant. However, catching-up of technological progress is a mediator variable between the introduction of high-tech talents and the labor income share at a significance level of 20%. While the confidence level is only 80 percent, it is worth noting that catching-up of technological advances helps to increase the labor income share.

Thus, the leapfrogging of technological progress helps to increase the capital income share, while the catching-up of technological progress helps to increase the labor income share. In 2019, China's Gini coefficient reached 0.465, still above the international alert line. If the income inequality gap can be narrowed, on the one hand, we should start from redistribution, improve the collection system of personal income tax, and increase the proportion of personal income tax in total tax. The primary means is to improve the education of workers because the catching-up of technological progress is manifested as technological diffusion. Also, the effectiveness of technology diffusion depends on whether the workers who learn technology have the ability to learn and whether they have the ability to use new production machines and participate in new production processes. If workers are well educated, their learning capacity increases accordingly.

It is found that the labor income share predicting by fractional Hausdorff grey model is increasing in 25 provinces and regions in China after 2018. This shows that the labor income share slows down the increase in income inequality gap after 2018, but the Gini coefficient of China is still above 0.46 after 2018 according to "China Statistical

Yearbook.” Therefore, there are other factors leading to the high-income inequality gap in China besides labor income share, for instance, urbanization level and traffic convenience.

The promotion of urbanization is also an important factor in assisting the catching-up of technological progress and increasing the labor income share. The higher the level of urbanization, the higher the concentration of labor, which is conducive to the spread of new technologies between labors. If workers gather together, then the frequency of knowledge exchange between them increases, and new technologies can be transmitted at the fastest speed. Then, workers in this region will increase their income due to the improvement of skills.

In addition, convenient transportation is also conducive to the spread of catching-up of technological progress. The speed at which new technologies are disseminated within regions depends on the agglomeration degree of labors, while the speed at which they are transmitted to other regions depends on the accessibility of traffic, such as the number of roads and railways between regions, so if a region is at a transport hub, it could become a distributing centre for advanced technology. Thus, taking advantage of this advantage, the region prioritizes access to advanced technologies from other regions and is likely to stimulate local economic growth, thereby boosting local income levels.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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