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Impact of Industrial Intelligence on Total Factor Productivity

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Abstract: Industrial intelligence is gaining more prominence in the new era of the technical revolution. This paper conducts an empirical test based on the panel data of 30 Chinese provinces (municipalities and autonomous regions) from 2006 to 2017. Firstly, the stochastic frontier analysis developed from the transcendental logarithmic production function is applied to calculate the total factor productivity of 30 provinces in China. The fluctuation of the total factor productivity is employed to reflect the quality of economic development. Secondly, the multilevel mediation model is applied to conduct the empirical test. Then, the robustness and endogeny of the conclusions are tested, and a further discussion is finally made, respectively, for eastern, central and western China. The results show that: (1) Industrial intelligence has a promoting effect on the improvement of total factor productivity. (2) Industrial intelligence can increase the demand for highly skilled labor and reduce the demand for low-skilled labor, but it has no significant impact on the demand for medium-skilled labor. (3) Industrial intelligence influences the improvement of total factor productivity through labor force structure.

Keywords: industrial intelligence; total factor productivity; the mediation effect model

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1. Introduction

Industrial intelligence is gaining more prominence in the new era of the technical revolution. China Manufacture 2025 (The Fifth Plenary Session of the 19th Central Committee of the CPC deliberated and adopted the Proposal of the Central Committee of the Communist Party of China on formulating the 14th Five Year Plan for National Economic and Social Development and the Vision of the Year 2035. Long Range Objectives through the Year 2035 means that China will basically realize socialist modernization by 2035) states that of promoting the development of intelligent manufacturing based on facilitating the merging of cyber technology and manufacturing. It is addressed in the report of the 20th National Conference of the CPC that "We will carry out industrial foundation reengineering projects and research projects on major technologies and equipment; support enterprises that use special and sophisticated technologies to produce novel and unique products; and move the manufacturing sector toward higher-end, smarter, and greener production". It is conceivable that intelligence manufacture will play a more important role in China's economic development and profoundly influence human society in the future.

The traditional economic development mode of China is facing unsustainable efficiency in the new era, such as a decreasing return on traditional investment and shrinking demographic dividend. There is a need to speed up accumulation to boost economic development. Labor shortage is driving the development of industrial intelligence. With the climbing-up of the current labor costs, replacing humans with machines has become an important way to increase production efficiency and stimulate the development of Chinese enterprises. The installation of industrial robots in China has risen by 36% from 2013 to 2017 [1].

In 2017, the Chinese government unveiled the Development Planning for a New Generation of Artificial Intelligence, pointing out the way forward for artificial intelligence (AI) and setting the goal of transforming the nation into a global hub for innovation in the field by 2030 [2]. In 2018, 390,000 industrial robots were manufactured globally, an increase

of 14.6% on the year before, while in China that number was 148,000, representing 38% of the world total and a growth of 14.7% year on year [3].

Industrial intelligence is also an important tool to respond to the aging population. Its development allows production tasks to be fulfilled by the capital instead of the labor, thus the increase of the investment return rate and whole-factor productivity. However, the investment-prone technical advancement would cause inter-substitution of the labor with different skills with the secondary industry and inclination of the general income to the capital, which would negatively impact the interests of the labor and the overall economic structure in the latter. How to promote high-quality growth and high-quality employment in the new era and how to promote Long-Range Objectives Through the Year 2035 with industrial intelligence are to be discussed in this paper.

2. Literature Review and Theoretical Framework

2.1. Industrial Intelligence and Economic Development

There is a general consensus in academia that industrial robots outperform human labor in both product quality and production efficiency [4,5] and can therefore boost the total factor productivity (TFP) in manufacturing and other industries in a meaningful way [6,7]. The view is that advances in AI and robot technology will automatically lead to faster and stronger economic growth [8–11].

As part of their research into the effect that AI has on economic growth, some scholars have in recent years turned their attention to the relationship between AI and TFP. According to [6], the latter serves as an important conduction mechanism through which the former plays its role in economic growth. Acemoglu and Restrepo reckon that AI can effectively respond to the impact of population aging and promote economic growth by elevating TFP [12,13].

Shackleton proposed that, as things stand, AI has only been able to raise the TFP of traditional manufacturing sectors but not that of some high-end ones [14]. Chen found that AI could aid in capital accumulation by improving the return on invested capital, thereby further increasing TFP [15]. Yang and Hou 's study based on industrial robot data of 72 countries over the period 1993–2017 proves that the increase in the utilization rate of industrial robots contributes to the increase of total factor productivity, thus promoting economic growth [16]. Based on panel data of 30 countries from 1995 to 2019, Cette et al. revealed that enhanced TFP through the application of industrial robots is a major driver behind the economic growth of developed countries [17]. It is estimated that AI has the potential to increase the annual GDP growth and labor productivity by 1.2 to 4% and 2%, respectively, higher than their long-term projections [18].

However, some researchers find that the industrial intelligence contributes little to the economic development or in an unnoticeable way.

As it takes time for disruptive innovation to have a significant impact on social productivity [5], the effect AI has on TFP exhibited a "convex first and then concave" shape. In the initial stages, AI may very well prove to be a drag on, rather than a booster for, TFP in the course of industrial restructuring due to the low penetration of industrial intelligence, inadequate infrastructure and outdated production systems. As AI gradually matures, TFP improves in leaps and bounds. At a certain point, however, AI will adversely affect TFP [19].

The contribution of the technology's advancement could not be raised if not synchronized with the improvement of the labor skills [20]. With the capital–skill complementarity hypothesis, the skillful labor force could make more contributions to the national economy and whole-factor productivity [21].

2.2. Industrial Intelligence and Labor Skill

The prevailing opinions of relevant studies are that industrial intelligence has a complementary or substitute effect on the labor force [22–26].

In the supplementary effect, the new employment posts grow with the development of the industrial intelligence and technology, and the productivity in some industries goes

upwards. In the substitution effect, the labor needs of the enterprises go downwards, and some traditional posts are replaced by the intelligent production.

Based on this proposition and the elasticity of the labor supply, the research shows that though the traditional posts lessen, more new employment posts appear [13]. Kanazawa et al. [27] point out that by substituting part of the low-skilled labor force and complementing the highly skilled labor force, industrial robots help drive the overall efficiency and reduce the time it takes to complete work. Sachs and Kotlikoff [28] note that the emergence of human–machine collaboration has transformed the manufacturing landscape by offering a viable solution to the shortage of skilled workers in the industry. As labor costs rise, the use of industrial robots to complement human labor will greatly enhance production efficiency and save time [29,30].

Yet many scholars, who examine the impact of industrial robots on the labor market, have argued that the application of such tools may result in wage reductions and a drop in employment in the manufacturing industry [31–34]. Recent years have seen many studies on how industrial robots have impacted employment in such countries as the United States [35,36], Japan [37] and France [38].

Another phenomenon of employment polarization occurs in the research of the employment structure of developed countries. There is an increasing demand for labor with high and low skills but decreasing demand for staff with medium skill level [39]. Without taking into consideration other factors, enterprises are inclined to "automation" with higher training cost or relatively simple work. In other words, the posts of great complexity or with low training cost, that is, the posts requiring high or low skills, could not easily be replaced by machines, and those with medium skills are more susceptible. Their difference of susceptibility to automation results in the polarized employment.

In China, there are three main viewpoints about the impact of industrial intelligence on Chinese labor skills, that is, the polarized employment in developed countries would also happen in China with the development of industrial automation, and it is a global trend of demanding more posts with low and high skills rather than medium skills [40,41]. Qu and Cheng found in their research of migrant labor that the employment posts with lowest and medium income are declining while those for high income are growing obviously [42]. The longer the enterprise applies industrial intelligence, the less the posts with low skills there will be [43]. For the researchers with the third viewpoint, they think there would be no large scale of unemployment because industrial automation is born with "tolerant innovation" [7,31]. Industrial intelligence is the endogenous choice growing from profit maximization, and the labor cost is closely related to industrial intelligence, so the analysis needs to be conducted on the results of the general equilibrium of the market [44].

From the literature review, we find that the current research is focused on industrial intelligence's relationship with either economic development or labor skills. They have provided a crucial theoretical foundation and evidence for our research. However, there exists some problems in the above-mentioned literature.

1. Difference in defining the concepts. Compared with "industrial intelligence" being discussed in this paper, most research is related with "technical advancement" or "artificial intelligence", covering all sectors in society, with more and more focus on the tertiary industry. There is a lack of overriding standards for choosing the principal variables.
2. Current research is mainly about the relationship between industrial intelligence and either economic development or labor skill, rarely about the combination of the three.
3. The research could lead to entirely different conclusions due to their different research angles and methods which result in their selection of different variables and empirical models.

3. Research Ideas and Framework

3.1. Research Ideas

The panel data of 30 provinces (municipalities, autonomous districts) from 2006 to 2017 are used for the empirical analysis in this paper. Tibet is not included because of data insufficiency. Firstly, the stochastic frontier analysis (SFA) developed from the

transcendental logarithmic production function is applied to calculate the total factor productivity (TFP) of 30 provinces (municipalities, autonomous districts) in China. With reference to Cai Fang and Wu Jinglian's methodology [45,46], the fluctuation of the total factor productivity is employed to reflect the quality of economic development; secondly, the multilevel mediation model is applied to conduct the empirical test [47]. Then, the robustness and endogeny of the conclusions are tested, and a further discussion is finally made, respectively, for eastern, central and western China.

3.2. Research Hypothesis

The following hypothesis is made in this article:

Hypothesis 1 (H1). *Industrial intelligence stimulates the growth of total factor productivity.*

Many features are shared by industrial intelligence and the past technical revolution. They could stimulate economic growth when promoting productivity in three aspects: (1) automation and substitution abate the labor demand of enterprises and simplify the complicated processes; (2) current labor force and capital are supplemented and enhanced with more qualified workers and effective capital investment; (3) spillover effect of the technology innovation radiates to the whole sector.

Hypothesis 2 (H2). *Industrial intelligence makes more demand of high-skilled labor and less for low-skilled labor, with little influence on the medium-level labor force.*

It is undeniable that development of industrial intelligence in China is still at the primary stage when compared with Western countries. In the meantime, the disparity of economic development and labor cost between coastal and inland areas makes its development uneven. As a result, the industrial intelligence development in China would entail some different features from Western countries. In this paper, the contribution of industrial intelligence to the Chinese economy is tested based on the differentiated labor structure.

Hypothesis 3 (H3). *Industrial intelligence impacts the whole-factor productivity through the level of labor skills.*

The capital–skill complementarity hypothesis refers to a phenomenon in which the high-skill post is more complementary with the capital than the low-skill post. The income of labor is strongly related to his/her skill level, which is measured by the academic credentials [48]. Similarly, skill-inclined technical advancement aggravates the inequality of income of differentiating and diverging skill levels and academic backgrounds. As far as the relationship between uneven income distribution and economic development, some researchers think the uneven income would restrain the sustainability of the economy [49], while others hold contrary opinions [50].

3.3. Creativity and Limitation of This Paper

Compared with current research, this paper makes the following marginal contribution by: (1) providing a systematic overview about the research of the impact of industrial intelligence on the Chinese labor structure; (2) extending the research to the quantitative analysis of the combination of industrial intelligence, labor structure and economic development; (3) providing theoretical support to realize the objectives of China Manufacture 2025 and the creation of a compatible labor force to the economic development.

The indicator system in this paper has to be adjusted due to the constraints of the data availability. The established level of industrial intelligence might have some deviation, since the number of the applied industrial robots at the provincial level is not published, and the industrial output data are not complete.

4. Calculation of Whole-Factor Productivity

4.1. Calculation Methods and Model Selection

Generally said, there are three different ways to calculate the whole-factor productivity (TFP): (1) growth accounting: the disadvantage of this method is estimating the stock of capital and labor; (2) non-parametric method: TFP is broken down into technical efficiency, scale efficiency and technical advancement (not so accurate with relative significance); (3) parametric method: commonly used to study the micro individual, such as SFA, OLS and FE. In this paper, the stochastic frontier analysis with the transcendental logarithmic production function is applied to calculate the total factor productivity (TFP) after testing the validity of functions [51,52].

The stochastic frontier analysis was applied early to analyze the panel data by Battese and Coelli [53], and its formula is as follows:

$$\ln Y_{it} = \ln f(x_{it}, \beta) + v_{it} - u_{it} \tag{1}$$

where Y_{it} is the actual output, and $f(x_{it}, \beta)$ is the output of enterprises when no efficiency is loss. v_{it} represents the random shock, if v_{it} follows the normal distribution, and u_{it} stands for technology without efficiency. u_{it} and v_{it} are considered to be independent from each other.

$$u_{it} = u_i \exp[-\eta(t - T)] \tag{2}$$

Battese and Coelli think u_i follows non-negative truncated distribution, that is, $u_i \sim N^+(\mu, \sigma_u^2)$, and η is the rate of change of u_{it}. As shown in Equation (2), the model in which u_{it} attenuates with the increase of time (t) is called stochastic frontier analysis under time-variation attenuation.

The initial model as shown in Equation (3) is established for this research:

$$\begin{gathered} \ln Y_{it} = \beta_0 + \beta_1 \ln L_{it} + \beta_2 \ln K_{it} + \beta_3 t + \frac{1}{2\beta_4 (\ln K_{it})^2} + \frac{1}{2\beta_5 (\ln L_{it})^2} \\ + \frac{1}{2\beta_6 t^2} + \beta_7 \ln K_{it} \ln L_{it} + \beta_8 t \ln L_{it} + \beta_9 t \ln K_{it} + v_{it} - u_{it} \\ u_{it} = \{u_{it} \exp[\eta(t - T)]\} \sim iidN^+(\mu, \sigma_u^2) \end{gathered} \tag{3}$$

In the above, K and L, respectively, stand for material capital and quantity of labor; v_i is random interference, u_i is the technology without efficiency and η is the time variation parameter of the technology efficiency. The production function is derived against t as follows:

$$\frac{\dot{Y}}{Y} = \frac{\partial lnf(X,t)}{\partial t} + \sum_j \frac{\partial lnf(X,t)}{\partial lnX_j} \frac{\partial lnX_j}{\partial X_j} \frac{dX_j}{dt} - \frac{\partial U}{\partial t} = \frac{\partial lnf(X,t)}{\partial t} + \sum_j \varepsilon_j \frac{\dot{X}_j}{Xj} - \frac{\partial U}{\partial t} \tag{4}$$

$$\dot{\mathrm{TFP}} = \dot{\mathrm{TE}}_{it} + \dot{\mathrm{TP}}_{it} + (E-1) \sum_j \frac{E_j}{E} \dot{X}_j \tag{5}$$

The calculation results are as follows:

$$\mathrm{TP}_{it} = \frac{\partial \ln Y_{it}}{\partial t} = \beta_3 + \beta_6 t + \beta_8 \ln l_{it} + \beta_9 \ln k_{it} \tag{6}$$

$$\mathrm{TE}_{it} = E[\exp(-u_i) \mid v_i - u_i] \tag{7}$$

$$\mathrm{SE} = (E-1) \sum_j \frac{E_j}{E} \dot{X}_{ij} (j = 1, 2) \tag{8}$$

$$E_j = \beta_j + \sum_{k \geqslant j} \beta_{jk} k + \beta_{jj} t (j = 1, 2) \tag{9}$$

In the above, $\dot{TFP}$ represents the increase rate of the total factor productivity, $\dot{TE}_{it}$ is for the rate of productivity change and TP_{it} for the technology advancement rate. $\dot{X}_j$ is the increase rate of the input factor "j", and E_j is the factor output elasticity.

4.2. Data Treatment

The panel data of the 30 provinces (municipalities and autonomous districts) in China are used to calculate TFP. However, Tibet is not included because of data deficiency. The data are treated as follows:

1. Output Y is represented as gross domestic production (GDP), and deflation is conducted based on the fixed price of the year 2006. The data source is *China Statistical Yearbook*.

2. Labor input L is expressed as effective labor input. Taking into consideration difference of labor qualification and internal structure of different provinces, the number of employees is not simply used as labor input but treated with average education years as follows:

$$EL_{it} = \frac{L_{it}}{E_{it}} \times E_{at} \tag{10}$$

Here, EL_{it} represents the input of effective labor of province i in year t, Lit represents the input of work input of province i in year t, Eit stands for the average years of education of the labor force of province i in year t and Eat for the national average years of education in year t. The data before 2011 are from different volumes of *China Statistical Yearbook*, and the data after 2011 are from the statistical yearbooks of each province. The missing data are obtained by supplementary calculation.

3. Capital input K is obtained by means of the perpetual inventory. The capital depreciation rate is differentiated by year (data from the research paper by Yu Yongze [52]), and the yearly material capital stock is calculated based on 2006.

4. Year 2006 is taken as the initial year, as "1" for time T, and 2017 as the end year as "12" accordingly.

Descriptive statistics of the variants is shown in Table 1 as follows.

Table 1. Descriptive statistics of variants related to TFP.

Variant	Symbol	Average Value	Standard Deviation	Maximum Value	Minimum Value
Output	lnY	8.959	0.964	6.143	10.963
Capital input	lnK	9.881	1.164	6.821	12.101
Labor input	lnL	7.59	0.81	5.673	8.814
Time	T	6.5	3.457	1	12
Square of capital input	KK	98.988	22.478	46.525	146.426
Square of labor input	LL	58.255	11.887	32.188	77.682
Square of time	TT	54.167	46.163	1	144
Capital input multiplied by labor input	KL	75.505	14.442	39.518	106.514
Time multiplied by capital input	TK	66.014	38.19	6.821	145.208
Time multiplied by labor input	TL	49.551	27.259	5.673	105.765

4.3. Modeling Estimation Results and Testing

The maximum likelihood estimator (MLE) is used in frontier 4.1 software to test the feasibility of the stochastic frontier analysis (SFA) to check if the inefficiency () exists or not. In other words, using the hypothesis H0: $\gamma = 0$, there is no inefficiency item if it is accepted, and OLS is more feasible; otherwise, SFA is more suitable.

The results are shown in Table 2. It shows that half indicators are prominent, and γ represents the portion of the inefficiency items in the total variance. The value of γ is 0.978 and very close to 1, so there exists inefficiency. In addition, under the prominence level

of 5%, the statistical amount of LR is more than 7.05, the threshold of mixed chi-square distribution. It supports the previous conclusion.

Table 2. Estimation results of SFA based on transcendental logarithmic production function.

Variant	Coefficient	Variant	Coefficient
C (constant)	9.567 *** (0.999)	TK (time multi.by capital)	−2.372 (0.620)
lnK (capital input)	2.113 ** (0.996)	TL (time multi.by labor)	2.841 *** (0.714)
lnL (labor input)	1.163 (0.997)	σ^2	0.246 (0.999)
T (time)	6.164 *** (0.998)	γ	0.978 (0.998)
KK (square of capital)	8.368 (0.381)	μ	321.19 *** (0.998)
LL (square of labor)	6.05 (0.587)	η	74.746 *** (0.993)
TT (square of time)	−14.464 ** (6.896)	log likelihood funct. value	370.61
KL (capital multi. by labor)	−0.151 (0.805)	LR statistical amount	930.472

Note: the numbers in brackets are the standard deviation; asterisks **, *** represent, respectively, the prominence levels of 5% and 1%. The sample observation value is 360.

4.4. Model Set-Up and Modification

The following two steps are made to further test and rectify the model and functions.

1. Test of production function: set up null hypothesis HO: $\beta_{KK} = \beta_{LL} = \beta_{TT} = \beta_{KL} = \beta_{TK} = \beta_{TL} = 0$. If it is accepted, the production function is a Cobb–Douglas function or the transcendental logarithmic production function to the contrary.

2. Test of technology change in the model: suppose all the coefficients containing the time variant are 0 and set up H0: $\beta_T = \beta_{TT} = \beta_{TK} = \beta_{TL} = 0$. If the hypothesis is accepted, there is no technology change in the production function; otherwise, the technology change does not exist.

The general likelihood ratio (LR) test is used in the above-mentioned two steps. $LR = -2\ln[L(H_0)/L(H_1)]$, and it follows χ^2 mixture distribution. If LR $> \chi^2_{1-0.05}(k)$, it rejects the null hypothesis; otherwise, the hypothesis is accepted.

From the first step in the Table 3, we could see that the test rejects the null hypothesis; therefore, the transcendental logarithmic production function is more feasible. The second step in the same table shows that the null hypothesis is accepted by the test, so there is a technology change in the production function, and all coefficients containing a time variant are 0.

Table 3. Test table for setting up models.

Test	Hypothesis	LLF	LR	Degree of Freedom K	$\chi^2_{1-0.05}(k)$	Conclusion
Step 1	H1: not all binomial coefficients are 0. H0: all binomial coefficients are 0.	370.61 329.099	83.022	3	7.05	HO rejected
Step 2	H1: not all time-varying coefficients are 0. H0: all time-varying coefficients are 0.	329.099 451.587	−244.976	3	7.05	HO accepted

Through the two-step test, the model is modified to be the SFA model with a non-time-variant transcendental logarithmic production function. It is presented in Formula (11):

$$\begin{gathered} \ln Y_{it} = \beta_0 + \beta_1 \ln L_{it} + \beta_2 \ln K_{it} + \frac{1}{2\beta_3(\ln K_{it})^2} + \frac{1}{2\beta_4(\ln L_{it})^2} \\ +\beta_5 \ln K_{it} \ln L_{it} + v_{it} - u_{it} \\ u_{it} = \{u_{it} \exp[\eta(t-T)]\} \sim iidN^+(\mu, \sigma_u^2) \end{gathered} \tag{11}$$

Without taking the technology advancement rate into consideration, the increase rate of the total factor productivity is shown in Formula (12):

$$\dot{\mathrm{TFP}} = \dot{\mathrm{TE}}_{\mathrm{it}} + (E-1)\sum_{j}\frac{E_j}{E}\dot{X}_j \tag{12}$$

The calculation results are:

$$\mathrm{TE}_i = E[\exp(-u_i) \mid v_i - u_i] \tag{13}$$

$$\mathrm{SE} = (E-1)\sum_{j}\frac{E_j}{E}\dot{X}_{ij}(j=1,2) \tag{14}$$

$$E_j = \beta_j + \sum_{k \geqslant j}\beta_{jk}k + \beta_{jj}t(j=1,2) \tag{15}$$

Here, $\dot{\mathrm{TFP}}$ represents the increase rate of the total factor productivity, $\dot{\mathrm{TE}}_{\mathrm{it}}$ is for the rate of productivity change and $\mathrm{TP}_{\mathrm{it}}$ is for the technology advancement rate. $\dot{\mathrm{X}}_{\mathrm{j}}$ is the increase rate of the input factor "j", and E_{j} is the factor output elasticity.

Therefore, the increase rate of the total factor productivity ($\dot{\mathrm{TFP}}$) of each province during the 12 years is obtained, and then the TFP is obtained.

5. Empirical Test

5.1. Mediation Effect

Mediation effect is a way to find out if the influence of an independent variable on the dependent will be affected by the mediator. Compared with the common OLS regression, this methodology could obtain profound results [47]. Specifically said, three regression equations are established to reflect the relations of the variables:

$$\mathrm{TFP}_{it} = \alpha_0 + \alpha_1 \ln t_{it} + \alpha_2\mathrm{Trade}_{it} + \alpha_3\mathrm{Df}_{it} + \alpha_4\mathrm{Sr}_{it} + \alpha_5\mathrm{Fra}_{it} + \varepsilon_{it} \tag{16}$$

$$\mathrm{Labor}_{it} = \beta_0 + \beta_1 \ln t_{it} + \beta_2\mathrm{Trade}_{it} + \beta_3\mathrm{Df}_{it} + \beta_4\mathrm{Sr}_{it} + \beta_5\mathrm{Fra}_{it} + \varepsilon_{it} \tag{17}$$

$$\mathrm{TFP}_{it} = \gamma_0 + \gamma_1 \ln t_{it} + \gamma_2\mathrm{Labor}_{it} + \gamma_3\mathrm{Trade}_{it} + \gamma_4\mathrm{Df}_{it} + \gamma_5\mathrm{Sr}_{it} + \gamma_6\mathrm{Fra}_{it} + \varepsilon_{it} \tag{18}$$

Gradually testing the regression coefficients, we take the three Equations of (16)–(18) as the three steps to test α_1 in Equation (16), β_1 in (17) and γ_1 and γ_2 in (18). If the coefficients α_1, β_1 and γ_2 are all prominent, there is a mediation effect. When γ_1 is not prominent, it is complete mediation. When γ_1 is prominent, it is partial mediation.

5.2. Principal Variables and Descriptive Statistics

1. Explained variable: the total factor productivity (TFP) is an important indicator to reflect the economic development level, and it is used as an explained variable in this paper. (Please see Chapter 4 for the detailed calculation.)

2. Mediating variable: The skill level of the labor force is reflected by the education degree. The labor force with primary or lower education background is viewed as having low skill, those with junior and senior high school education as having medium skill and high skill for those with college and higher education (reference to Sun Zao and Hou Yulin [54] for this classification). The data are from volumes of *China Labor Statistical Yearbook*.

3. Explanatory variables: with reference to the research by Sun Zao and Hou Yulin [54] and by Chen Xiao, Zheng Yulu and Yao Di [55], the explanatory variables are:

(1) The index of industrial intelligence is used to represent the level of industrial intelligence, and the data come from the principal component analysis calculation performed by Su Zao and Hou Yulin [54]. The indicators include infrastructure construction, production application, competitiveness and benefit. Under them are more specific indicators, namely software popularization and application, intelligent equipment input,

information-collecting capacity, data treatment and storage capacity, enterprises with intelligent manufacturing, new products, platform operation and maintenance, creativity and economic and social benefits.

(2) The trade openness of each province is measured by the ratio of total imports and exports to its GDP; the financial development is measured by the ratio of deposits and loans to GDP, and the upgrading of industrial structure is measured by the ratio of the increased value of the tertiary industry to GDP. The road miles per square kilometer are to reflect the infrastructure status. The data source is the statistical yearbook of each province and the CSMAR databank.

The descriptive statistics of the principal variables are listed in Table 4 (Please refer to Appendix B for the visualization chart of relevant data on total factor productivity, education level and trade development of each province).

Table 4. Descriptive statistics of principal variables.

Variable	Symbol	Average Value	Standard Deviation	Maximum Value	Minimum Value
Total factor productivity	TFP	1.261	0.731	2.661	−0.130
Industrial intelligence	lnt	15.995	9.863	76.686	2.152
Low-skill labor	low	0.253	0.102	0.603	0.026
Medium-skill labor	mid	0.590	0.005	0.764	0.341
High-skill labor	high	0.141	0.005	0.559	0.030
Trade openness	Trade	0.311	0.020	1.662	0.016
Financial development	Df	2.855	0.059	8.131	1.288
Industrial structure upgrade	Sr	0.430	0.005	0.802	0.283
Infrastructure	Fra	0.858	0.025	2.438	0.066

5.3. Regression Results

The fixed effects model is chosen after the Hausman test. By controlling the fixed effects of region and time, the first step is taken to test the mediation effect, and the OLS estimation results are presented in Table 5, in which column (1) is the separate regression of the total factor productivity (TFP) and the industrial intelligence level (Int); in column (2) the new variable "financial development" (Df) is added; industrial structure (Sr) is added in column (3); infrastructure (Fra) is added in column (4); and trade openness (Trade) is added in column (5).

The gradual regression results of Table 5 reveal that industrial intelligence keeps its distinct and positive effects on the total factor productivity with stable coefficients. They have proved H1 that industrial intelligence could promote the total factor productivity, increasing the productivity of enterprises and their capital accumulation. In the meantime, column (5) in the table exhibits that the lower the financial development and trade openness, the higher the total factor productivity. This might result from the unsound financial system in China and being at the end of supply chain for a long time. The total factor productivity is higher when the portion of the tertiary industry is higher and infrastructure is better. It fits into the current mainstream perception. Upgrading the industrial structure meets the need of economic development and creates new demand; thus, the operational efficiency of the economy is increased. The improvement of the infrastructures is helpful for exerting the effects of agglomeration and diffusion, reducing the costs and boosting learning and extension of new technologies.

The second step of the mediation effect is taken to test H2, that is, industrial intelligence could entail more demand for high-skill labor, and less demand for low-skill labor, but without prominent influence on the medium-skill labor. This hypothesis is proved when the prominence level is at 1%. The testing results are shown in Table 6 (1), (3) and (5).

However, we should be aware that when industrial intelligence is used as an explanatory variable, its coefficient is very small. The fact behind this is there is a great deal of substitution and innovation with the technical advancing of Chinese enterprises. The au-

tomation of factories would oust a certain part of the low-skill labor force, but the occurring new posts would accommodate some low-skill labor. During this process, we could only see a narrow range of increasing demand for high-skill labor.

The third step is to test H3, that is, industrial intelligence would influence the total factor productivity through labor structure. The testing results are presented in Table 6 (2), (4) and (6). When the prominence level is at 1%, there is an obvious correlation between industrial intelligence and high-skill labor. Specifically said, a one-unit increase of the industrial intelligence would bring about a 0.054-unit increase of the total factor productivity but with a 0.0015-unit decrease (3.826× 0.004) caused by high-skill labor, so it is a partial mediation effect. In addition, there is a distinct correlation of the total factor productivity with the industrial intelligence and medium-skill labor but weak correlation between the industrial intelligence and medium-skill labor. Therefore, thereis no mediating effect between medium-skill labor and the total factor productivity. It is the same for low-skill labor and the total factor productivity.

Table 5. Regression results of OLS.

	TFP (1)	**TFP (2)**	**TFP (3)**	**TFP (4)**	**TFP (5)**
Lnt (industrial intelligence)	0.077 ***	0.082 ***	0.100 ***	0.098 ***	0.054 **
	(0.023)	(0.023)	(0.022)	(0.022)	(0.023)
Df		−0.497 ***	−1.055 ***	−0.991 ***	−0.968 ***
(financial develp.)		(0.165)	(0.181)	(0.185)	(0.179)
Sr			10.489 ***	10.348 ***	10.547 ***
(industrial structure)			(1.696)	(1.694)	(1.646)
Fra				1.044	1.257 *
(infrastructure)				(0.662)	(0.644)
Trade					−2.280 ***
(trade openness)					(0.511)
C	−3.121 ***	−0.010	−4.688 ***	−6.149 ***	−2.067
(constant)	(0.897)	(1.363)	(1.495)	(1.756)	(1.935)
Fixed effect of region	Control	Control	Control	Control	Control
Fixed effect of time	Control	Control	Control	Control	Control
R^2	0.851	0.855	0.871	0.879	0.880
OBS	360	360	360	360	360
F	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***

Note: the numbers in brackets are the standard deviation; asterisks *, **, *** represent, respectively, the prominence levels of 10%, 5% and 1%. The sample observation value is 360.

The progressive analysis of industries by Dai Xiang, Liu Meng and Ren Zhicheng divides Chinese industrial enterprises into different types. The development of the resource-based industry and primary industry would be constrained with improving skills of the labor force, which, however, would promote the development of low-, medium- and high-technical industrial development, and its impact would be enhanced with industrial progress [56]. The second column of Table 6 shows that high-skill labor would lower the total factor productivity, and it sounds unreasonable but actually reveals the dominance of resource-based and primary industries in China, which have low demand for highly educated and high-skill human resources.

In order to test the above conclusion, 200 times of sampling and testing have been conducted by means of Bootstrap, and the results are shown in Table 6. As far as the high-skill labor is concerned, there is obvious indirect and direct effects, and it provides proof for the partial mediation effect. For the medium- and low-skill labor force, there exists only a direct effect instead of indirect effect, and the absence of a mediator is proved. Above all, the industrial intelligence would influence the economic development through labor structure and specifically influence the total factor productivity through the demand of high-skill labor.

Table 6. Regression results of mediation effect model.

	High-Skill Labor (1)	TFP (2)	Medium-Skill Labor (3)	TFP (4)	Low-Skill Labor (5)	TFP (6)
lnt (industrial intelligence)	0.004 *** (0.001)	0.243 *** (0.017)	0.001 (0.001)	0.227 *** (0.015)	−0.007 *** (0.001)	0.223 *** (0.014)
high (high skill)		−3.826 *** (1.442)				
mid (mid skill)				1.491 * (0.781)		
low (low skill)						−0.808 (0.660)
Bootstrap test (indirect effect)	0.015 ** (0.007)		0.001 (0.001)		0.006 (0.005)	
Bootstrap test (direct effect)	0.243 *** (0.027)		0.227 *** (0.026)		0.223 *** (0.027)	
Df (financial development)	0.024 *** (0.005)	−1.060 *** (0.136)	0.050 *** (0.008)	−1.076 *** (0.140)	0.032 *** (0.009)	−1.125 *** (0.135)
Sr (ind. str. upgrading)	0.277 *** (0.064)	3.849 ** (1.770)	−0.117 (0.103)	2.962 * (1.737)	−0.327 *** (0.124)	2.524 (1.755)
Fra(infrastructure)	−0.003 (0.007)	0.516 *** (0.186)	−0.020 * (0.011)	0.497 *** (0.188)	−0.020 (0.013)	0.510 *** (0.188)
Trade (trade openness)	−0.004 (0.011)	−2.030 *** (0.285)	0.080 *** (0.017)	−0.805 *** (0.280)	−0.013 (0.021)	−2.024 *** (0.288)
C (constant)	−0.103 *** (0.017)	0.250 (0.474)	−0.728 *** (0.027)	−0.440 (0.792)	0.434 *** (0.032)	0.996 * (0.554)
R^2	0.746	0.563	0.312	0.559	0.403	0.668
OBS	360	360	360	360	360	360
F	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***

Note: the numbers in brackets are standard deviation; asterisks *, **, *** represent respectively the prominence levels of 10%, 5% and 1%.

5.4. Robust and Endogenous Test

5.4.1. Endogenous Test

The endogenous test is carried out in two ways, as shown below:

1. In order to control the endogenous omitted variable bias, the following variables are added: the financial input of R&D of each province is used to measure the input of R&D (Rd), and the imported value of industrial equipment is to measure the investment of machines and equipment (Fdi). The first step test is made by combining these two additional variables with the previous explanatory variable. The results given in Table 7 show that the prominence level of different coefficients is under good control, and the coefficient of the industrial intelligence, being consistent with that of Table 5, is positive. The consistency of the conclusions is therefore guaranteed.
2. The OLS regression is carried out in the second step to solve the reverse causality of two variables, i.e., industrial intelligence and labor skill, by the methodology of Mao Qilin and Sheng Bin [57], in which the industrial intelligence is an explained variable, and the explanatory variables include trade openness, financial development, industrial structure upgrading, infrastructure, R&D input, equipment investment and labor skill. The results in Table 8 exhibit that the prominence level of the industrial intelligence and other explanatory variables except labor skill is within 10%, and the correlation of the industrial intelligence and the labor skill (high, medium and low) is not prominent. This eliminates, to some extent, the possibility of reverse causality between industrial intelligence and labor skill.

Table 7. OLS regression results with additional explanatory variables.

	TFP		TFP
lnt (indus. intelligence)	0.088 *** (0.021)	Rd (R&D input)	0.324 *** (0.037)
Df (financial developt)	−0.889 *** (0.159)	Fdi (equipment invest.)	−0.144 *** (0.046)
Sr (indus.str.upgrading)	8.799 *** (1.456)	C (constant)	−10.324 *** (1.969)
Fra (infrastructure)	0.379 (0.574)	Fixed effect of region	control
Trade (trade openness)	−1.792 *** (0.461)	Fixed effect of time	control
OBS	360	R^2	0.906

Note: the numbers in brackets are standard deviation; asterisks *** represent respectively the prominence levels of 1%.

Table 8. Test results of reverse causality.

	Industrial Intelligence		Industrial Intelligence
Df (financial developmnt)	1.178 *** (0.412)	high (high-skill labor)	20.121 (11.638)
Sr (indus. str. upgrade)	−12.227 *** (4.039)	mid (medium-skill labor)	−5.174 (10.960)
Fra (infrastructure)	2.546 * (1.512)	low (low-skill labor)	0.116 (11.941)
Trade (trade openness)	−6.860 *** (1.309)	C (constant)	45.912 *** (11.141)
Rd (R&D input)	−0.270 *** (0.093)	Fixed effect of region	Control
Fdi (equip. investment)	0.179 (0.123)	Fixed effect of time	Control
OBS	360	R^2	0.974

Note: the numbers in brackets are standard deviation; asterisks *, *** represent respectively the prominence levels of 10% and 1%.

5.4.2. Robust Test

The robust test is carried out by converting the model to moderation analysis. For the convenience of explaining coefficients, the mean centering is conducted for the two variants, i.e., industrial intelligence and labor skill, before producing interaction by multiplication (lh = lnt*high, lm = lnt*mid, ll = lnt*low). The results of the empirical test are displayed in Table 9. In the first column (1) of the table, the industrial intelligence (lnt) and interaction (lh) is correlated, so the moderation effect exists. One unit increase of the industrial intelligence would increase the total factor productivity by 0.239 unit. One unit increase of the interaction would decrease the total factor productivity by 0.417 unit. This means the high-skill labor would weaken the total factor productivity. Both moderation and mediation reach the same conclusion. The conclusion of this paper is proved to be robust by the moderation of the mediator, the high-skill labor.

Table 9. Regression results of moderation.

	TFP (1)	TFP (2)	TFP (3)
lnt (indus. intelligence)	0.239 *** (0.014)	0.264 *** (0.013)	0.217 *** (0.016)
high (high skill)	−1.742 (1.283)		

Table 9. *Cont.*

	TFP (1)	TFP (2)	TFP (3)
lh (lnt*high)	−0.417 *** (0.042)		
mid (medium skill)		3.363 *** (0.751)	
lm (lnt*mid)		0.639 *** (0.055)	
low (low skill)			0.532 (0.805)
ll (lnt*low)			0.271 *** (0.069)
Df (financial development)	−0.806 *** (0.122)	−0.755 *** (0.120)	−1.102 *** (0.131)
Sr (indus. str. upgrade)	4.706 *** (1.509)	2.607 * (1.437)	4.369 ** (1.722)
Fra (infrastructure)	0.344 ** (0.170)	0.427 *** (0.165)	0.365 * (0.192)
Trade (trade openness)	−2.593 *** (0.285)	−3.794 *** (0.308)	−2.007 *** (0.318)
Rd (R&D input)	0.110 *** (0.018)	0.103 *** (0.017	0.078 *** (0.020)
Fdi (equip. investment)	−0.120 *** (0.037)	−0.166 *** (0.035)	−0.186 *** (0.041)
C (constant)	−0.836 ** (0.425)	−2.647 *** (0.681)	0.031 (0.625)
R^2	0.687	0.704	0.604
OBS	360	360	360
F	0.000 ***	0.000 ***	0.000 ***

Note: the numbers in brackets are standard deviation; asterisks *, **, *** represent respectively the prominence levels of 10%, 5% and 1%.

6. Region-by-Region Test

In view of the fact that there is a great disparity between different regions with respect to economic development, industrial intelligence and labor education, the 30 provinces (municipalities, autonomous districts) are divided into three regions for the research, namely east, middle and west. As shown in Table 10, in the first step, the control variants are generally at the prominence level of no more than 10% after the mediation replicate for the three regions, and the coefficient of the industrial intelligence is positive and prominent. So, the regression is under a good control. The hypothesis (H1) that industrial intelligence promotes total factor productivity stands the test. The industrial intelligence coefficient gradually reduces from the east to the middle to the west region.

The research conducted by other people concludes that the impact of intelligence on the intensive economic development is from prohibition to promotion in a "U" shape, and the stimulating effect is more distinguished in the east region [58]. This might be attributable to the excellent market environment and technology in the east. The results of Table 10 are not only compatible with this conclusion but also prove further that the turning point of the "U" shape has been transcended in the east, middle and west regions, though with different positions.

Table 10. OLS regression results region by region.

	East	Middle	West
Lnt (industrial intelligence)	0.235 ***	0.206 ***	0.153 ***
	(0.024)	(0.020)	(0.015)
Df (financial development)	−2.001 ***	−0.056	−0.233 **
	(0.286)	(0.122)	(0.105)
Sr (industrial structure upgrade)	9.284 ***	2.868 *	5.407 ***
	(3.564)	(1.457)	(1.479)
Fra (infrastructure)	1.280 ***	3.163 ***	−0.992 ***
	(0.402)	(0.253)	(0.186)
Trade (trade openness)	−2.731 ***	1.875	0.810
	(0.472)	(1.699)	(0.837)
Rd (R&D input)	0.066 **	−0.109 ***	0.039
	(0.029)	(0.032)	(0.025)
Fdi (equip. investment)	−0.197 ***	−0.108 **	0.330 ***
	(0.065)	(0.044)	(0.075)
C (constant)	−0.201	−4.180 ***	−2.269 ***
	(0.892)	(0.595)	(0.576)
R^2	0.610	0.916	0.690
OBS	360	360	360
F	0.000 ***	0.000 ***	0.000 ***

Note: the numbers in brackets are standard deviation; asterisks *, **, *** represent respectively the prominence levels of 10%, 5% and 1%.

In the second step of the test with the mediation replicate for the three regions, the results of Table 11 show that for the east region, the industrial intelligence could increase the demand for high-skill labor and reduce the demand for low-skill labor; for the middle region, influenced by industrial intelligence, the demand for the labor with medium and high skills goes up while the demand for the low-skill labor drops down; similarly, for the west region, the demand for the labor with medium and high skills also goes up. This conclusion is quite similar to Hypothesis 2 (H2) with a minor difference. The positive correlation remains for high-skill labor and industrial intelligence, the not-prominent coefficient of medium-skill labor turns out to be prominent and the prominence varies with different regions. This difference might be caused by the different labor cost. Because of relatively high labor cost, the enterprises in the east region are in more urgent need of reducing the labor cost by adopting intelligence; so, they are more intent toward automation with higher training cost or relatively simple work, and the posts for the medium-skill labor are more easily replaced. On the contrary, there is sufficient labor resources in the middle and west regions, so the enterprises in these two regions are less interested in the intelligence, and the substitution effect of the industrial intelligence is not obvious for their medium-skill labor.

From the third step of the mediation replicate test for the three regions, we could see that the high-skill labor would reduce the total factor productivity in the east and west regions; the medium-skill labor would increase the total factor productivity in the east and middle regions; and the low-skill labor would make the total factor productivity in the east and middle regions decline but make the total factor productivity in the west boost. This conclusion extends the previous hypothesis (H3): the industrial enterprises in the west region mostly stay at the primary stage, being either a labor-intensive or resource-extracting type, so their demand for the low-skill labor is higher than the medium and high skills. Although most enterprises are the primary ones in the middle and east regions, they are more developed than the west; so, their demand for the medium-skill labor is higher than the low- and high-skill labor. This implies that the industrial intelligence in the west is at the primary stage with more low-skill laborers, while the industrial intelligence in the middle and east regions develops to the medium level with more skillful workers.

Table 11. Mediation regression results region by region.

Region		High-Skill Labor	TFP	Medium-Skill Labor	TFP	Low-Skill Labor	TFP
East	lnt	0.002 ** (0.001)	0.255 *** (0.024)	−0.004 *** (0.001)	0.271 *** (0.024)	−0.001 (0.001)	0.232 *** (0.024)
	high		−10.046 *** (2.441)				
	mid				9.740 *** (2.089)		
	low						−4.342 * (2.222)
Middle	lnt	0.008 *** (0.001)	0.080 *** (0.027)	0.006 ** (0.003)	0.192 *** (0.020)	−0.015 *** (0.003)	0.168 *** (0.023)
	high		3.342 (2.270)				
	mid				2.539 *** (0.926)		
	low						−2.489 *** (0.854)
West	lnt	0.008 *** (0.001)	0.202 *** (0.016)	0.009 *** (0.002)	0.155 *** (0.017)	−0.020 (0.002)	0.186 *** (0.019)
	high		−6.222 *** (1.170)				
	mid				−0.213 (0.841)		
	low						1.696 *** (0.604)

Note: the numbers in brackets are standard deviation; asterisks *, **, *** represent respectively the prominence levels of 10%, 5% and 1%. (All regression models have stands F test; the output results of other variants are not presented in Table 11 due to limited space; please see Appendix A for the complete table).

7. Conclusions and Recommendations

The empirical test was carried out in this paper based on the panel data of 30 provinces (municipalities, autonomous districts) in China from 2006 to 2017. Firstly, the stochastic frontier analysis (SFA) with a transcendental logarithmic production function was employed to calculate the total factor productivity (TFP) of the 30 provinces (municipalities, autonomous districts). Referring to the methodology of Cai Fang and Wu Jinglian, the variation of the total factor productivity reflects the quality of economic development. Secondly, with reference to the research of Wen Zhonglin and Ye Baojuan, the empirical test was conducted with a mediation effect model, which is followed by the robust and endogenous tests of the results. Finally, further study is taken for the east, middle and west regions. The results show that:

1. As far as the whole nation is concerned, the industrial intelligence could boost the total factor productivity. This conclusion is still plausible after the region-by-region test, and the boosting effect diminishes from the east to the west. This is explained by the "U"-shaped impact of the intelligence on the intensive economic development. With intensifying marketization and improving economic environment, the boosting effect would be enhanced.

2. As far as the whole nation is concerned, industrial intelligence would increase the demand of high-skill labor and decrease the demand of low-skill labor, with little influence on the medium-skill labor. It is found from the region-by-region test that the high-skill labor and the industrial intelligence always maintain a positive correlation, but the not-prominent coefficient of medium-skill labor becomes prominent, and it is negative for the east region and positive for the middle and west regions. The regional disparity of the medium-skill labor variant could be explained by the phenomenon of "employment polarization". In other words, the higher labor cost in the east region presses the enterprises

there to reduce the labor cost by adoption of the intelligence, and they have preference toward "automation" with higher training cost or the relatively simple work; thus, the medium-skill labor would be more easily replaced by automated machines. However, there is sufficient labor resources in the middle and west regions at present, so the enterprises there are less motivated to use the intelligence technology to substitute the medium-skill labor and thus the weak influence of the industrial intelligence on the medium-skill labor.

3. As far as the whole nation is concerned, the industrial intelligence increases the total factor productivity through the labor structure. Specifically said, the mediating effect of the high-skill labor would lower the total factor productivity, that is, the demand of the enterprises for the high-skill labor is not high. The region-by-region test reveals that the enterprises in the middle and east regions demand more of medium-skill labor but less of the low- and high-skill labor. In the west, because most enterprises are primary labor-intensive and resource-extracting enterprises, their demand of the low-skill labor is higher than the medium- and high-skill labor. However, the primary enterprises in the middle and east regions are more developed than the west, so their demand of the medium-skill labor is higher than the low- and high-skill labor. This implies that the industrial intelligence in the west is at the primary stage with more low-skill laborers, while the industrial intelligence in the middle and east regions develops to the medium level with more skillful workers.

Industrial intelligence is an endogenous choice by enterprises to maximize profit. With increasing labor cost, adoption of industrial intelligence becomes more and more cost-effective, and the momentum of development would be enhanced. In the face of this trend, we should fully recognize the great significance of technical innovation to China's economic development and enhance the research and development investment in the relative fields. There is no one-size-fits-all policy, and we need to be aware of the regional disparity. In the meantime, we should keep our core value of making the staff irreplaceable by strengthening the vocational training of the low-skill labor and creating adaptive working posts.

In addition, there are still limitations in this paper, which are manifested in the single measurement of industrial intelligence indicators. At present, in addition to using the principal component analysis method for measurement, many scholars have used IRF's industrial robot data. Some scholars have used patent data, data mining methods, etc. We will make up for this deficiency in the next step of research.

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Appendix A

Table A1. Mediation regression results region by region (complete table).

Region		High	TFP	Mid	TFP	Low	TFP
East	lnt	0.002 **	0.255 ***	−0.004 ***	0.271 ***	−0.001	0.232 ***
		(0.001)	(0.024)	(0.001)	(0.024)	(0.001)	(0.024)
	high		−10.046 ***				
			(2.441)				
	mid				9.740 ***		
					(2.089)		
	low						−4.342 *
							(2.222)

Table A1. *Cont.*

Region		High	TFP	Mid	TFP	Low	TFP
	Df	0.028 ***	−1.720 ***	−0.018 *	−1.823 ***	0.005	−1.979 ***
		(0.009)	(0.280)	(0.011)	(0.271)	(0.010)	(0.283)
	Sr	0.391 ***	13.212 ***	−0.072	9.989 ***	−0.554 ***	6.881 *
		(0.114)	(3.518)	(0.131)	(3.341)	(0.131)	(3.739)
	Fra	0.046 ***	1.745 ***	−0.019	1.464 ***	−0.054 ***	1.046 **
		(0.013)	(0.398)	(0.015)	(0.378)	(0.015)	(0.416)
	Trade	−0.056 ***	−3.301 ***	0.101 ***	−3.719 ***	0.022	−2.633 ***
		(0.015)	(0.469)	(0.017)	(0.490)	(0.017)	(0.470)
	Rd	0.002 **	0.085 ***	−0.003 ***	0.094 ***	0.002 **	0.075 **
		(0.001)	(0.028)	(0.001)	(0.028)	(0.001)	(0.029)
	Fdi	0.003	−0.168 ***	−0.003	−0.168 ***	−0.001	−0.202 ***
		(0.002)	(0.062)	(0.002)	(0.061)	(0.002)	(0.064)
Middle	lnt	0.008 ***	0.080 ***	0.006 **	0.192 ***	−0.015 ***	0.168 ***
		(0.001)	(0.027)	(0.003)	(0.020)	(0.003)	(0.023)
	high		3.342				
			(2.270)				
	mid				2.539 ***		
					(0.926)		
	low						−2.489 ***
							(0.854)
	Df	0.027 ***	−0.146	0.035 **	−0.146	−0.076 ***	−0.245 *
		(0.007)	(0.136)	(0.016)	(0.121)	(0.017)	(0.133)
	Sr	0.052	2.696 *	−0.828 ***	4.972 ***	0.589 ***	4.335 ***
		(0.080)	(1.449)	(0.187)	(1.586)	(0.202)	(1.467)
	Fra	0.001	3.160 ***	−0.018	3.210 ***	−0.020 ***	3.114 ***
		(0.014)	(0.250)	(0.032)	(0.241)	(0.035)	(0.240)
	Trade	−0.110	2.241 ***	−0.466 **	3.058 *	0.662 ***	3.522 **
		(0.093)	(1.702)	(0.219)	(1.676)	(0.235)	(1.704)
	Rd	−0.004 **	−0.096 ***	−0.009 **	−0.087 ***	0.016 ***	−0.070 **
		(0.002)	(0.033)	(0.004)	(0.032)	(0.004)	(0.033)
	Fdi	−0.006 **	−0.088 **	−0.016 ***	−0.068	0.017 ***	−0.065
		(0.002)	(0.046)	(0.006)	(0.044)	(0.006)	(0.044)
West	lnt	0.008 ***	0.202 ***	0.009 ***	0.155 ***	−0.020	0.186 ***
		(0.001)	(0.016)	(0.002)	(0.017)	(0.002)	(0.019)
	high		−6.222 ***				
			(1.170)				
	mid				−0.213		
					(0.841)		
	low						1.696 ***
							(0.604)
	Df	0.005	−0.203 **	−0.072 ***	−0.248 **	0.070 ***	
		(0.007)	(0.096)	(0.011)	(0.122)	(0.015)	
	Sr	0.077	5.883 ***	−0.311 *	5.341 ***	0.018	−0.352 ***
		(0.103)	(1.342)	(0.159)	(1.508)	(0.214)	(0.111)
	Fra	−0.071 ***	−1.433 ***	−0.038 *	−1.000 ***	0.131 ***	−1.214 ***
		(0.013)	(0.188)	(0.020)	(0.189)	(0.027)	(0.197)
	Trade	−0.043	0.539	−0.055	0.798	0.145	0.563
		(0.058)	(0.759)	(0.090)	(0.841)	(0.121)	(0.819)
	Rd	−0.001	0.039 *	0.008 ***	0.041	−0.008 **	0.053 **
		(0.002)	(0.023)	(0.003)	(0.026)	(0.004)	(0.025)
	Fdi	−0.008	0.280 ***	−0.030 ***	0.324 **	0.040 ***	0.262 ***
		(0.040)	(0.068)	(0.008)	(0.881)	(0.011)	(0.077)

Note: the numbers in brackets are standard deviation; asterisks *, **, *** represent respectively the prominence levels of 10%, 5% and 1%.

Appendix B

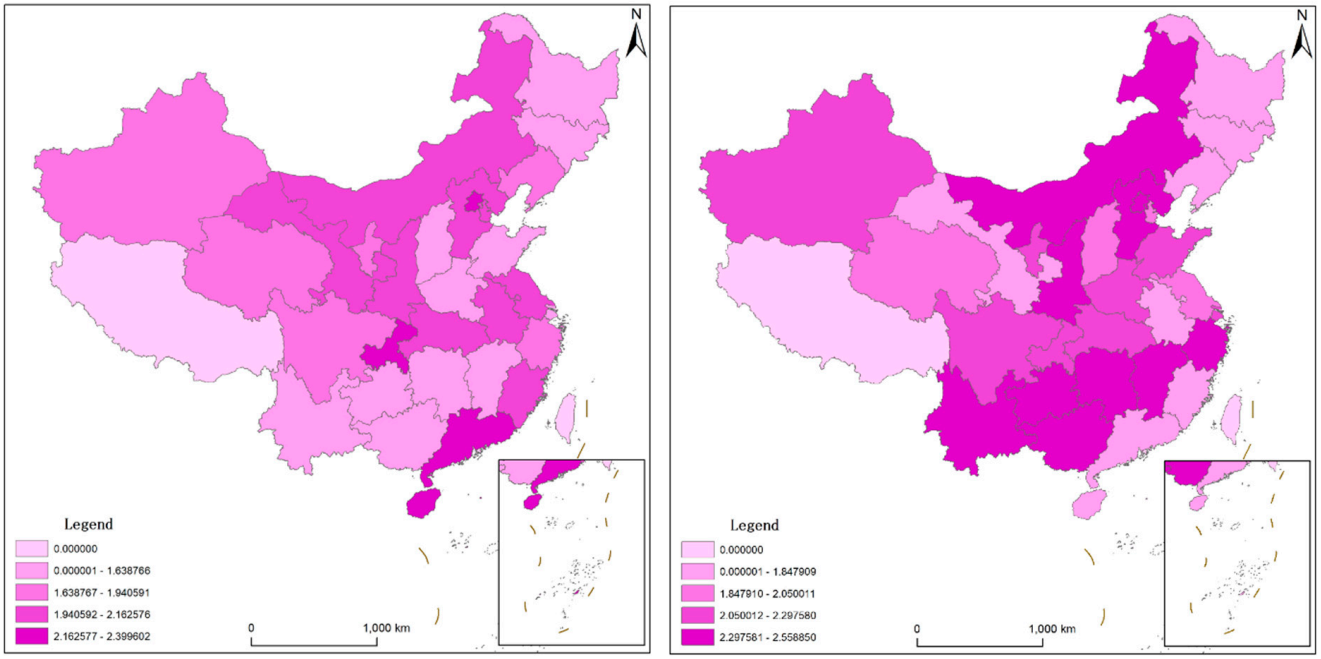


Figure A1. Total factor productivity in each province (rhe left picture shows the situation in 2006, and the right picture shows the situation in 2017, the same below).

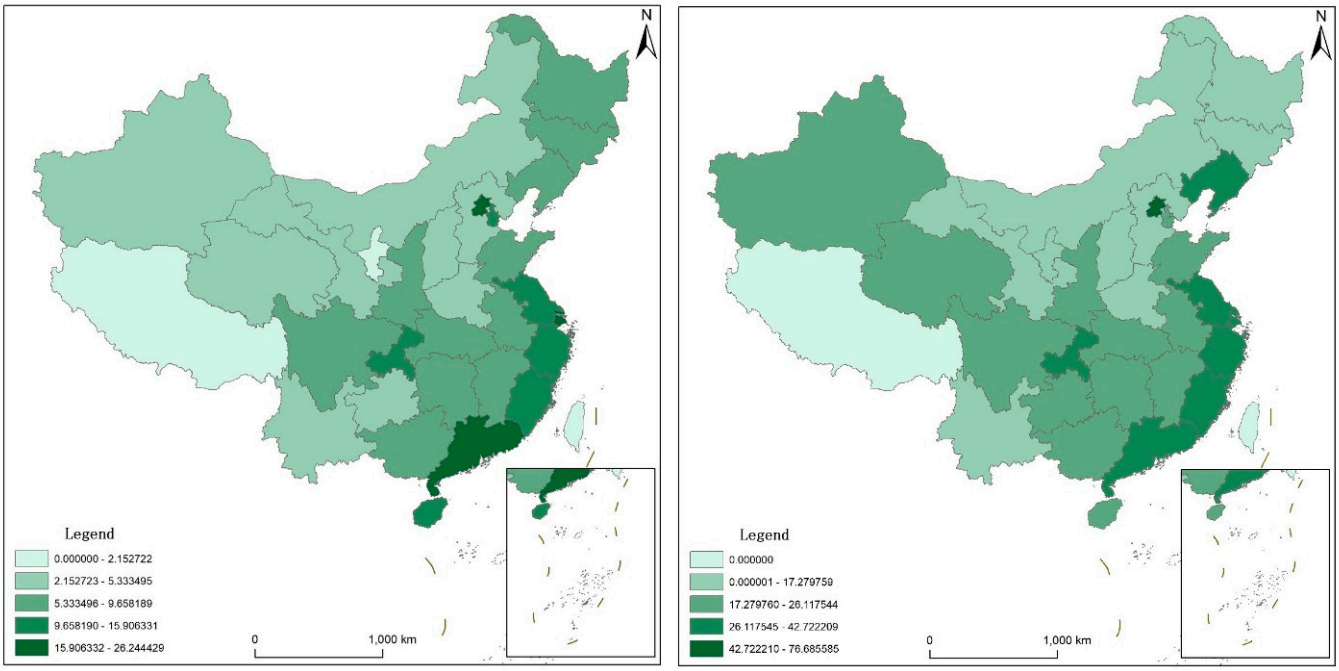


Figure A2. Industrial intelligence in each province.

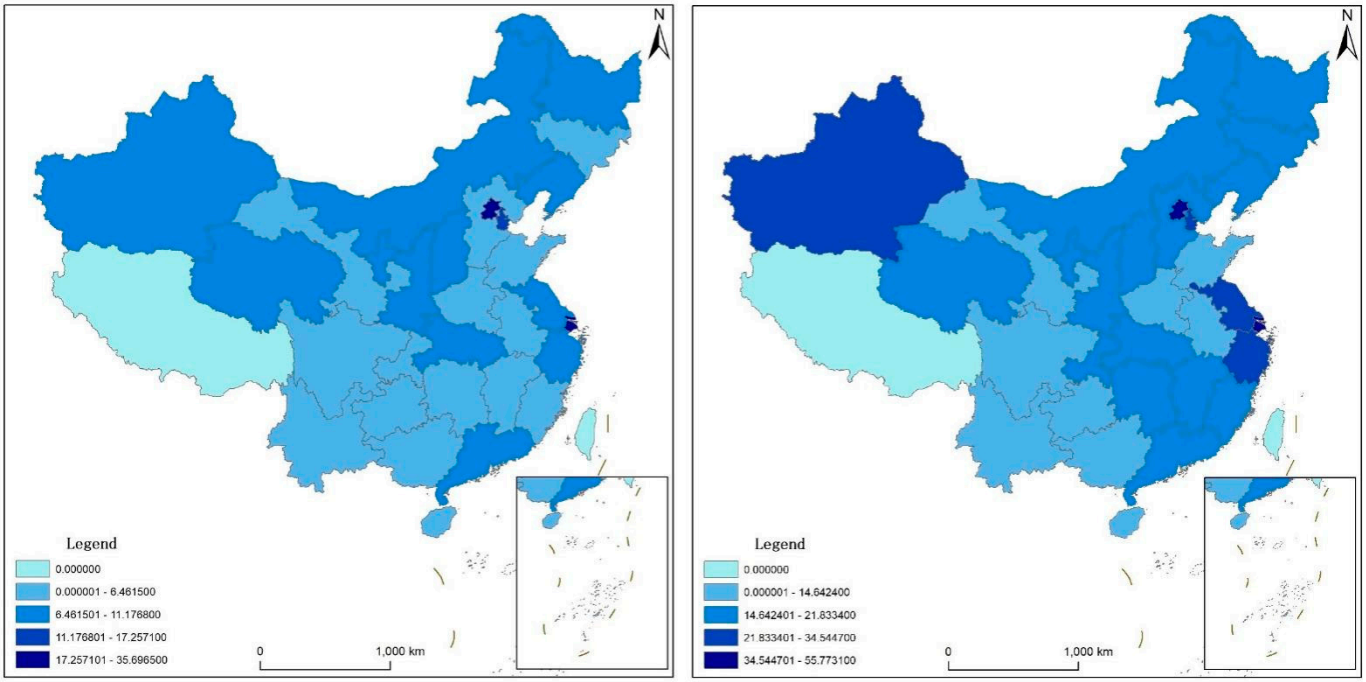


Figure A3. High-skilled labor force in each province.

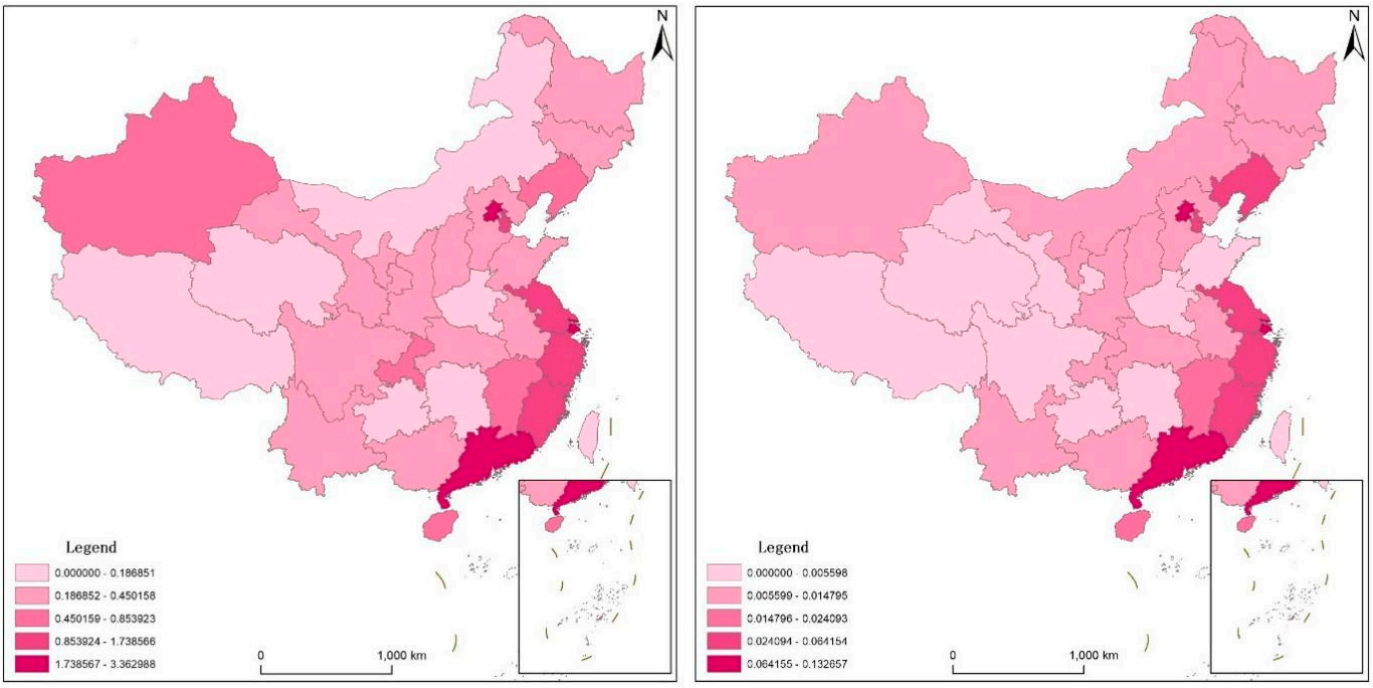


Figure A4. Degree of trade liberalization in each province.

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