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The sources of the evolution of China's provincial economic gap: a green economic growth accounting perspective

Wenju Yang and Ruiyun Long

Abstract
The inter-provincial economic gap in China is obvious and tends to expand, although it is still unclear why this occurs. This paper combines DEA-based green economic growth accounting, growth convergence test and distribution dynamic analysis to show that China's inter-provincial labor productivity demonstrated significant growth convergence between 1997 and 2016, while it was significantly promoted by capital deepening and obviously inhibited by technological progress and human capital accumulation, and the effect of technological efficiency change remained unclear. In addition, the gap of labor productivity level in China's provinces widened significantly, which can be largely attributed to the combined effects of technological progress and capital deepening. The economic growth accounting analysis ignoring Energy and environmental factors tends to overestimate the relative contribution of factor accumulation and underestimate that of TFP changes, while ignoring human capital will lead to opposite biased results, but both of which do not change the qualitative conclusions mentioned above.

JEL O18 O47 R11
Keywords Counterfactual analysis; distribution dynamic analysis; green economic growth accounting; multimodal test; non-parametric test

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1 Introduction

Since the reform and "opening up", China's economic development has been acknowledged across the world. But regional economic gaps have generally widened. Statistics suggest that the variation coefficient of mainland China's GDP (including autonomous regions, municipalities and provinces) was as high as 0.8102 in 2018, which represented an increase of 34.27 percent on the 1978 figure (0.6034), and was also slightly higher than the 2017 figure (0.8049). [①] A report published after the Communist Party of China's 19th National Congress observes that China's economy has entered a stage of high-quality development after a period of rapid growth, and also notes that major contradictions in society have "transformed into the contradiction between the people's increasing needs for a better life and the imbalanced and inadequate development". It is obvious that the promotion of balanced regional development is an important task for China's high-quality development. It is therefore important to explore evolutions within the emergence and development of China's regional economic gap, and to identify its underpinning factors.

Since the 1990s, a large number of studies have sought to address the formation of these gaps. However, due to different research purposes, objects, methods or data, they have produced divergent research conclusions (see Tan and Li（2004）and other reviews of the literature). Economic growth accounting research decomposes the source of economic growth into factor accumulation and TFP(Total Factor Productivity) changes, [②] with the intention of directly analyzing the evolution of regional economic gaps at the factor level. This has important implications for the decision-making reference values that guide the formulation and implementation of coordinated economic development strategies at the regional level.

In reflecting on research ideas and methods, the related literature observes the following. First, an accounting analysis of Neoclassical economic growth that ignores environmental factors (Li et al., 2006). Second, a Neoclassical economic growth accounting that considers environmental factors (Chen, 2010). Third, Stochastic Frontier Analysis (SFA) of economic growth accounting that ignores environmental factors (Hao, 2006). Fourth, Data Envelopment Analysis (DEA) for economic growth accounting that ignores environmental factors (Yang, 2006; Henderson et al., 2007). Finally, DEA analysis for economic growth accounting that considers environmental factors (Yang, 2001 & 2015; Zhu, 2014).

Of these, economic growth accounting approaches based on DEA and SFA fully acknowledge the phenomenon of technological inefficiency in economic development, which is more consistent with the actual reality of economic development. However, most studies do not incorporate environmental factors into their analysis, which may lead to a biased measure of productivity growth (Chung, et al., 1997), and this can in turn produce an incorrect estimate of the relative contribution of factor accumulation and TFP change. In addition, related studies that consider environmental factors basically stop at the multiple decomposition of economic growth sources in which the green TFP research lacks a complete economic growth accounting analysis, and there is no in-depth analysis of the evolutionary trend or distribution dynamics of economic growth sources, which means it is not possible to explain the actual factors that underpin the evolution of the regional economic gap. It should also be noted that Zhu(2014), after drawing on the measurement and decomposition results of

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[①] The original 1978 data is taken from the *China's GDP historical data 1952-1995*, while the rest of the data is taken from the *National Bureau of Statistics of China*.

[②] Factor accumulation can be further decomposed into capital deepening and human capital accumulation; TFP changes can be further decomposed into technological efficiency changes and technological progress; Technological efficiency changes include pure technological efficiency changes, scale efficiency changes, and allocation efficiency changes. Technological progress includes biased technological and neutral technological progress.

green TFP and applying variance decomposition analysis, finds that factor input is the main reason for the widening of the per capita GDP gap in China. Li et al.(2006), after a variance decomposition with Neoclassical economic growth accounting results, find that the huge TFP gap between provinces is the fundamental reason for the widening of the labor productivity gap. These studies draw on economic growth accounting research to examine how China's regional economic gap emerged and developed, but they still have some aspects that deserve further exploration. For example, when Zhu(2014) analyzes the source of regional economic gap, green economic growth accounting is only used to calculate TFP and its constituent factors, while the components of other relevant regional economic gaps are directly derived from variance decomposition. It should be asked if this method will affect the conclusions, and it should also be recognized that his study does not consider the role of human capital. Li et al.(2006) ignore technological inefficiency and environmental factors, which is important as this may affect the conclusions that they draw. In addition, they only engage with the period up to 2002, and therefore fail to provide insight into recent changes in the evolution of China's regional economic gap.

In recent years, a group of studies (see Henderson et al.,2007; Enflo and Hjertstrand, 2009; Badunenko et al.,2013; and Barnabé,2016) have introduced human capital into DEA-based economic growth accounting, and use the β convergence test and dynamic distribution analysis to explore the role that capital deepening, human capital accumulation, technological progress and technological efficiency changes have on the evolution of international or regional economic gaps. Badunenko et al.(2013) also discuss the "polarization" phenomenon of global productivity distribution, although this contribution lacks rigorous statistical testing.[③] Henderson et al.(2008) rectify this shortcoming by performing a multimodal test on the "cluster" phenomenon of global income distribution. This group of studies are based on economic growth accounting, and they seek to explore the role of sources of economic gaps. Some studies also analyze the phenomenon of "polarization", and draw on a new perspective to provide an in-depth analysis of the sources that drive changes in China's economic gaps. But with the exception of Henderson et al.(2007), none of the studies discuss issues related to China's regional economic gap, and none incorporate energy and environmental factors into their analysis. It is still unknown if this will affect their research conclusions. [④]

In summary, it can be ascertained that existing research into the sources of China's regional economic gaps is inconclusive and, as the contributions of Li et al.(2006) and Zhu(2014) underline, sometimes contradictory. An assessment that engages at the stage of innovation-driven high-quality development clarifies that it is necessary to further explore the factors that underpin changes in China's economic gap by drawing on the perspective of economic growth accounting. This contribution, it is anticipated, will considerably the formulation of relevant policies. We propose that existing research needs to be improved in the following ways.

First, related research that draws on economic growth accounting does not fully consider energy, environmental and human capital factors. It is still open to question if this will affect research conclusions, and so further discussion is required. This paper draws on the DEA-based green economic growth accounting to simultaneously incorporate desired output, energy, human capital, labor, physical capital and undesired output

[③] "Cluster" and "polarization" are equivalent, and in this instance are understood to refer to the variable distribution that extends from unimodal to multimodal distribution. This interpretation is more consistent with the literature than the one offered by Duclos et al.(2004).Microeconomic analysis also tends to offer a much narrower definition of "polarization", which excludes psychological meanings such as individual alienation and group internal identification.

[④] The Mass Balance Principle suggests that when undesired output variables (e.g. environmental variables) are introduced into the production function, corresponding input variables (e.g. energy variables) should be introduced at the same time.

with the intention of offering a more comprehensive analysis of the accumulation of input factors and TFP changes, along with their respective roles as constituent elements in the evolution of China's provincial labor productivity gap. We conduct a robustness analysis by comparing results that ignore energy-related, environmental or human capital factors with our conclusions.

Second, existing research does not offer a specific analysis of the existence of labor productivity "polarization" in China. In drawing on the results of green economic growth accounting, this paper comprehensively applies counterfactual labor productivity analysis and multimodal test with the intention of statistically testing if there is a "polarization" phenomenon in the evolution of China's inter-provincial labor productivity gap. In addition, it also seeks to analyze if capital deepening, human capital accumulation, technological progress, changes in technological efficiency, or any combination of these factors has contributed to a "polarization" trend in labor productivity.

In engaging with the existing research and the entry points of the growth rate and level of labor productivity, this paper seeks to offer a new explanation of the source of China's regional economic gaps. The results show that unilateral factor accumulation or TFP changes do not sufficiently explain the evolution of China's inter-provincial economic gaps during the period 1997-2016. It therefore contends that these changes should be attributed to combined effects, and suggests that particular emphasis should be placed on the roles of capital deepening and technological progress. This differs from the perspective offered by "factor accumulation" (Li et al.,2006) or "TFP changes" (Zhu,2014). There is a significant absolute β convergence in the growth rate of China's provincial labor productivity, and capital deepening plays a significant role in promoting it, technological progress and human capital accumulation have a significant inhibitory effect (the former is particularly obvious), and the impact of changes in technological efficiency is not obvious. The joint promotion of capital deepening and technological progress (the role of human capital accumulation and technological efficiency change is very small), has significantly increased the labor productivity gap in China's provinces, but there has not been any observed phenomenon of labor productivity "polarization". The robustness analysis also shows that, irrespective of if energy, environmental or human capital factors are considered, the comprehensive analysis framework that this this paper uses consistently reaches the same qualitative conclusions.

The remainder of the paper is organized as follows: A second part briefly introduces the DEA-based green economic growth accounting model before the third part explains the variables and data that will be applied during empirical analysis; the fourth part conducts multiple decomposition analysis of the economic growth of Chinese provinces. The fifth part combines the β convergence test, kernel density map, and non-parametric test of unknown distribution, and engages from the growth rate and level of labor productivity to analyze the sources of the evolution of China's inter-provincial economic gaps. The multimodal test is also combined and a statistical analysis seeks to ascertain if the phenomenon of "polarization" exists. The final part then briefly summarizes the paper.

2 DEA Model for green economic growth accounting

The economic growth accounting analysis with non-parametric method can be traced as far back as research into international economic gaps conducted by Kumar and Russell(2002). In drawing on the TFP measurement and decomposition of Färe et al.(1994), they decompose labor productivity growth into three major sources, specifically capital deepening, technological progress and technological efficiency changes. Timmer and

Los(2005) use sequential DEA to improve this approach, and this means their results are not affected by technological regress. Henderson and Russell(2005) later offer a quadruple decomposition model that incorporates human capital. Yang(2011 & 2015) draw on this research and introduces energy and environmental factors to construct a triple and quadruple decomposition model of green economic growth accounting.

This paper applies the quadruple decomposition model of green economic growth accounting to empirical analysis, and will now briefly introduce its features.

2.1 Construction of production frontier with sequential DEA and DDF

Suppose there are N input variables $x \in R^N$, M desired output variables $y \in R^M$, and I undesired output variables $b \in R^I$ in the economy. Presuming that production technology meets the three major assumptions of free disposability of desired output, weak disposability of undesired output and zero jointness of desired output and undesired output, production technology can be represented by Directional Distance Function (DDF) through the use of Equation (1) and Figure (1) .

$$\vec{D}_o(x,y,b;g) = \sup\{\beta : (y,b) + \beta g \in P(x)\} \tag{1}$$

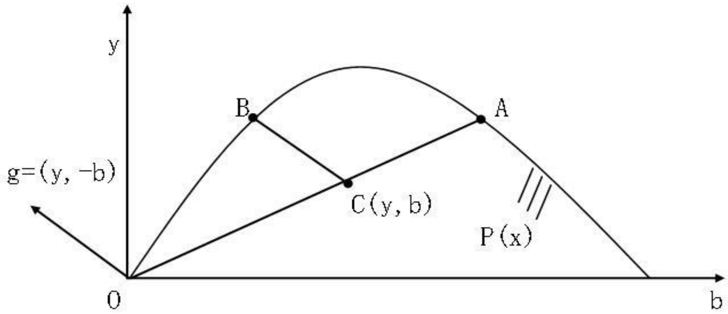


Figure 1 Schematic diagram of directional distance function

In Equation (1) and Figure 1, *C (y, b)* is the decision unit that corresponds to the output set *(y, b)*, *P (x)* is the production possibility set, g = *(y, -b)* is the direction vector of the desired and undesired outputs and β is the value of the directional distance function. According to the aforementioned directional distance function, when the number of inputs is constant, the improvement of technological efficiency will simultaneously increase the quantity of desired outputs and decrease the quantity of undesired outputs.

In order to determine the economy's production frontier, which is the curve 0BA in Figure 1, all decision-making units on the economy's best practice frontier need to be determined. In order to avoid the collapse of the production frontier, which is otherwise referred to as "technological regress", the production frontier of period t is constructed by using all input and output data of period t and before, which makes it possible to determine the value of the distance function of the decision unit by solving the nonlinear programming shown in Equation (2). The best practice frontier is then constructed on this basis. Of these, K is the number of decision-making units, $\vec{D}_o^t\left(x^t, y^t, b^t; y^t, -b^t\right)$ is the directional distance function of the observation value k' in period t, while the best practice frontier is composed of all decision-making units whose distance function value β is 0.

$$
\begin{aligned}
&\overrightarrow{D}_o^t(x^t, y^t, b^t; y^t, -b^t) = \max \beta \\
&s.t. \\
&\sum_{k=1}^{K}\sum_{\Gamma=1}^{t} z_k^{\Gamma} y_{km}^t \geq (1+\beta) y_{k'm}^t, m = 1,\cdots,M \\
&\sum_{k=1}^{K}\sum_{\Gamma=1}^{t} z_k^{\Gamma} b_{ki}^t = (1-\beta) b_{k'i}^t, i = 1,\cdots,I \\
&\sum_{k=1}^{K}\sum_{\Gamma=1}^{t} z_k^{\Gamma} x_{kn}^t \leq x_{k'n}^t, n = 1,\cdots,N \\
&z_k^{\Gamma} \geq 0, k = 1,\cdots,K, \Gamma = 1,\cdots,t
\end{aligned}
\tag{2}
$$

2.2 Multiple decomposition of labor productivity growth

Equation (2) is the distance function calculation formula with the inputs and production technology of period *t*. This also makes it possible to obtain the distance function calculation formula of the inputs of period t (or *t-1*) under the production technology of period *t-1* (or *t*). Subsequent to calculating the directional distance function value β of each decision unit and taking into account energy and environmental constraints, labor productivity growth can be decomposed into *TFP* change *TFPC* (the product of the change in technological efficiency *EC* and technological progress *TC*) and factor accumulation *KHC* (the product of capital deepening *KC* and human capital accumulation *HC*). See formula (3).

$$
\begin{aligned}
\frac{y_c}{y_b} &= \frac{e_c}{e_b} \times \left[\frac{\bar{y}_c(\hat{k}_c)}{\bar{y}_b(k_c)} \times \frac{\bar{y}_c(\hat{k}_b)}{\bar{y}_b(k_b)}\right]^{1/2} \times \left[\frac{\bar{y}_b(\tilde{k}_c)}{\bar{y}_b(\hat{k}_b)} \times \frac{\bar{y}_c(\hat{k}_c)}{\bar{y}_c(\tilde{k}_b)}\right]^{1/2} \times \left\{\left[\frac{\bar{y}_b(\hat{k}_c)}{\bar{y}_b(\tilde{k}_c)} \times \frac{\bar{y}_c(\tilde{k}_b)}{\bar{y}_c(\hat{k}_b)}\right]^{1/2} \times \frac{H_c}{H_b}\right\} \\
&= (EC \times TC) \times (KC \times HC) \\
&= TFPC \times KHC
\end{aligned}
\tag{3}
$$

In Equation (3), e_b and e_c are the technological efficiency of the base period *b* and the current period *c;* $\hat{y}_b$ and $\hat{y}_c$ are the effective labor productivity in periods *b* and *c*, that is, labor productivity adjusted by human capital; $\bar{y}_b(\hat{k}_b) = \hat{y}_b / e_b$ and $\bar{y}_c(\hat{k}_c) = \hat{y}_c / e_c$ are the potential effective labor productivity in the two periods; $\bar{y}_c(\hat{k}_b)$ and $\bar{y}_b(\hat{k}_c)$ are respectively the potential effective labor productivity of period *b* under the technological frontier of period *c* and the potential effective labor productivity of period *c* under the technological frontier of period *b;* and *H* represents human capital, with $\tilde{k}_b = K_b / (L_b \times H_c)$ and $\tilde{k}_c = K_c / (L_c \times H_b)$ being two effective capital-labor ratio from a counterfactual perspective; meanwhile, $\bar{y}_c(\tilde{k}_b)$ and $\bar{y}_b(\tilde{k}_c)$ provide a counterfactual perspective of the corresponding potential effective labor productivity.

3 Variables and data

According to the empirical analysis of the green economic growth accounting model introduced in Part 2, input and output variables and their associated data need to be first selected. This paper applies the relevant research approach and draws on available data to select the Gross Domestic Product (*GDP*) of China's provinces as the desired output variable and the province's industrial SO_2 as the undesired output variable. The number of employees (*L*) is the labor input variable, the human capital stock per labor (*H*) is the human capital input variable, the provincial physical capital stock (*K*) is the physical capital input variable, and the province's total energy consumption (*E*, converted by standard coal) is the energy input variable. With the exception of the physical capital and human capital stock, all data are taken from the *China Economic Network*, the *China Statistical Yearbook*, the *China Environmental Statistics Yearbook*, the *China Energy Statistics Yearbook* and the *Chongqing Statistical Yearbook*. Some statistical data from the early (such as those related to sulfur dioxide emissions) and recent (such as those related to the annual average number of employees in the province) periods is lacking, and it should also be recognized that Chongqing became a municipality in 1997, which is important because the time span of all analysis data extends from 1997 to 2016. In addition, the Tibet Autonomous Region's energy consumption data cannot be obtained from the government's public data, and it is therefore excluded from the analysis of mainland China's 30 provinces and regions.

The data acquisition of physical capital stock and human capital stock will now be briefly introduced.

3.1 Stock of physical capital

Related studies have applied the Perpetual Inventory Method or the Capital Price Lease Measurement Method to physical capital stock data, although the former has been used more frequently. Jing(2013) proposes that when the depreciation amount of fixed assets is known, Equation (4) should be used to calculate the physical capital stock data, because this will help to avoid the artificial selection difference of the depreciation rate. Of these, *K*, *P*, *I* and *D* respectively represent physical capital stock, fixed asset investment price index, nominal investment amount and fixed asset depreciation amount, and t represents time. This paper uses Jing's inter-provincial physical capital stock data for the year 1995 and applies Equation (4) to calculate *K* for each of China's provinces during the period 1997-2016. Relevant basic data is taken from the *Chinese GDP Accounting Historical Data 1952-2004* and the *China Statistical Yearbook*.

$$K_t = K_{t-1} + \left(I_t - D_t\right) \div P_t \tag{4}$$

3.2 Stock of human capital

Academics use different methods to measure human capital stock data. This paper uses the widely applied method of return rate on education to calculate the average human capital stock of labor. In Equation (5) and (6), *i* is the province, t is the period, *E* is the number of years of education, *H* is the human capital, $p_{i,j}^{t}$ is the number of the jth level of education in year t of province *i*, and $edu_{i,j}^{t}$ is the number of years at the jth level of education during year t in province *i*.

$$E_i^t = \sum_{j=1}^{5} \frac{edu_{i,j}^t \times p_{i,j}^t}{\sum_{j=1}^{5} p_{i,j}^t} \left(i = 1 \cdots 30, j = 1 \cdots 5\right) \tag{5}$$

$$H_i^t = e^{\phi\left(E_i^t\right)} \left(i = 1 \cdots 30\right) \tag{6}$$

In order to calculate the average human capital stock of labor in accordance with Equation (5) and (6), it is necessary to classify education levels and the corresponding average years in education, and then determine the specific form of function $\phi\left(E_i^t\right)$ along with the return rate of education at different levels. In drawing on

Peng(2005) , this paper divides education level into five categories, specifically illiterate and semi-illiterate, primary, junior high, high, tertiary and above, and sets corresponding years of education as 1.5, 6, 9, 12 and 15+. $\phi\left(E_i^t\right)$ is set as a piecewise linear function, and data on China's education return is determined as follows: the coefficient of years of education between 0-6 years is 0.18, 0.134 for between 6-12 years and 0.151 for more than 12 years. Data is also required on the proportion of the labor. This paper refers to the proportion of the labor force referenced in the *China Labor Statistics Yearbook*.

Table 1 shows the general statistical descriptions of the related variables(see Appendix Table A1 for the sample data). It will be noted that each variable value varies significantly. With the exception of the human capital variable, the standard deviations of other variables are close to (or even greater than) their medians and averages, while the maximum and minimum ratio of the human capital variable is as high as 3.03. During the period 1997-2016, the number of inputs, output scale and economic growth rate in China's provinces varied greatly, and so did the environmental impact of each of these factors. It is clearly necessary to incorporate energy input, human capital, and emission pollutants into the analytical model when measuring the relative contribution that economic growth sources make to the development of China's provinces.

Table 1: Data: summary statistics

Variable	**Unit**	**Maximum**	**Minimum**	**Median**	**Mean**	**Standard deviation**
GDP	100 million yuan	58 191.70	205.68	4 930.48	10 218.15	12 542.62
SO_2	10 000 tons	149.67	1.69	35.03	41.61	29.07
K	100 million yuan	160 048.30	1 141.67	11 742.36	35 207.73	40 808.67
L	10 000 people	6 726.39	235.40	2 023.51	2 448.29	1 632.74
H	year	8.92	2.94	4.48	4.50	1.03
E	10 000 tons of standard coal	26 933.33	390.30	6 035.52	7 412.75	5 612.80

Notes: The authors have calculated all table data. The *GDP* and physical capital stock data are respectively adjusted with the *GDP* deflator and the fixed asset investment price index, and the base period is 2000.

4 Multiple decomposition of labor productivity growth in Chinese provinces

4.1 Construction of production frontiers

Solving the nonlinear programming shown in Equation (2) makes it possible to obtain the distance function values for each province during the period 1997-2016, and calculate their technological efficiency on this basis (see Figure 2). It is noticeable that technological inefficiency was widespread in the economies of Chinese provinces and there were also large disparities between provinces. In 1997, Fujian, Guangdong, Hainan and Shanghai were leaders in production, while Ningxia had the lowest level of technological efficiency (only 0.5252). Almost 20 years later, only Shanghai and Guangdong remained among the leaders, and Ningxia again recorded the lowest score (a slight decrease to 0.5094). In addition, the technological efficiency change of different provinces varied between 1997 and 2016. The technological efficiency of the 14 provinces either increased or decreased, and the national mean score increased from 0.7260 to 0.7316.

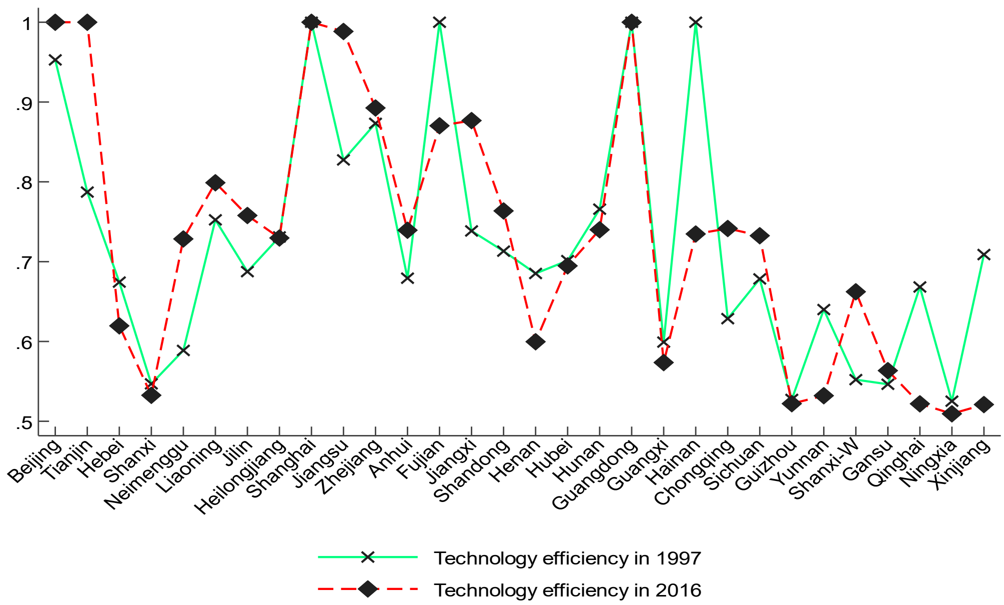


Figure 2: Technology efficiencies of Chinese provinces

Notes: The authors have calculated all figure data with MaxDEA.

4.2 Accounting for green economic growth

Combining Equation (2) and (3) makes it possible to multi-decompose the labor productivity changes in each province between 1997 and 2016. The results shown in Table 2 make it possible to draw the following conclusions:

(1)The labor productivity of each of China's provinces has greatly improved (by an average of 455.20 percent), but there are still large inter-provincial gaps. The maximum and minimum ratios of labor productivity growth rates are as high as 3.37, and the standard deviation is as high as 1.4034, which is close to one-third of its average. Shaanxi-W, Chongqing and Neimenggu are ranked as the top three for growth rate of labor productivity, and have each increased by a factor of more than 7; in contrast, the growth of labor productivity in Beijing, Hainan, Shanghai and Xinjiang has been slower, and their growth rates have not even tripled.

(2)The economic growth of China's provinces results from the "two-wheel" drive of factor accumulation and TFP progress, and extensive economic growth is still very obviously apparent. Capital deepening, human capital accumulation, technological progress and changes in technological efficiency have all contributed to the growth of labor productivity, and have respectively increased labor productivity by 190.82 percent, 9.46 percent, 85.74 percent, and 1.22 percent. Factor accumulation has promoted labor productivity by 214.21 percent, which is nearly 2.5 times the contribution of TFP progress. Capital deepening is obviously still the main source of economic growth in China's provinces in recent years , and the characteristics of extensive economic growth are very obviously apparent.

Table 2: The results of green economic growth accounting

Province	***LPC***	***TFPC***			***KHC***		
		Total	***EC***	***TC***	***Total***	***KC***	***HC***
Beijing	3.4274	4.0658	1.0495	3.8740	0.8430	0.5847	1.4418
Tianjin	5.7760	3.0186	1.2704	2.3761	1.9134	1.9529	0.9798
Hebei	5.0734	1.5197	0.9187	1.6542	3.3385	3.4345	0.9721
Shanxi	4.8847	1.4219	0.9738	1.4600	3.4354	3.1956	1.0751
Neimenggu	8.1434	1.9897	1.2371	1.6083	4.0928	3.5847	1.1418
Liaoning	5.3195	1.8911	1.0617	1.7811	2.8129	2.6621	1.0567
Jilin	5.8916	1.9745	1.1023	1.7912	2.9839	2.9282	1.0190
Heilongjiang	4.6330	1.7208	0.9981	1.7240	2.6924	2.5355	1.0619
Shanghai	3.4883	2.9168	1.0000	2.9168	1.1959	1.0110	1.1829
Jiangsu	6.2832	2.2860	1.1946	1.9136	2.7485	2.7237	1.0091
Zhejiang	4.9718	2.0283	1.0221	1.9844	2.4512	2.1522	1.1389
Anhui	5.4337	1.6701	1.0885	1.5343	3.2536	3.3089	0.9833
Fujian	4.4115	1.6386	0.8703	1.8827	2.6923	2.2743	1.1838
Jiangxi	5.6676	1.7595	1.1873	1.4819	3.2211	3.1089	1.0361
Shandong	5.4789	1.8315	1.0707	1.7106	2.9914	2.6191	1.1422
Henan	5.1774	1.5425	0.8752	1.7624	3.3566	3.2062	1.0469
Hubei	6.4989	1.7414	0.9906	1.7578	3.7321	3.3599	1.1108
Hunan	6.5640	1.5592	0.9664	1.6135	4.2097	3.7934	1.1098
Guangdong	4.4411	1.9758	1.0000	1.9758	2.2478	2.0225	1.1114
Guangxi	6.1398	1.6642	0.9573	1.7384	3.6892	3.5353	1.0435
Hainan	3.8941	1.9588	0.7347	2.6661	1.9880	1.9431	1.0231
Chongqing	8.6202	1.9817	1.1797	1.6798	4.3499	4.1178	1.0564
Sichuan	6.9928	1.7319	1.0797	1.6040	4.0376	3.8917	1.0375
Guizhou	7.3581	1.5180	0.9899	1.5335	4.8472	4.8911	0.9910
Yunnan	4.5995	1.3674	0.8314	1.6447	3.3638	3.1195	1.0783
Shanxi-W	8.6814	2.0393	1.1995	1.7001	4.2571	3.4951	1.2180
Gansu	5.0531	1.5424	1.0313	1.4956	3.2762	3.2592	1.0052
Qinghai	5.4837	1.3715	0.7809	1.7563	3.9983	3.3061	1.2094
Ningxia	4.8901	1.3414	0.9699	1.3830	3.6457	2.9139	1.2511
Xinjiang	3.2819	1.2632	0.7349	1.7189	2.5981	2.3144	1.1226
Mean	5.5520	1.8777	1.0122	1.8574	3.1421	2.9082	1.0946
S.D.	1.4034	0.5764	0.1400	0.5069	0.9201	0.8865	0.1001

Notes: The authors have calculated all table data with MaxDEA. *LPC* denotes cumulative change of labor productivity, and *EC, TC, KC, HC, TFPC,* and *KHC* denote cumulative labor productivity changes caused by changes in technological efficiency, technological progress, capital deepening, human capital accumulation, TFP changes, and factor accumulation respectively. Mean and S.D. are the means and standard deviations.

(3)The sources of labor productivity growth in China's provinces are quite different. Technological progress promotes labor productivity growth in all provinces, but other sources of economic growth show diversified characteristics. Of these, technological efficiency shows the largest inter-provincial difference, which causes the standard deviation of the changes in labor productivity to be 0.1400, which is much larger than the average value of 0.0122. The largest improvement in technological efficiency is Tianjin, which shows a 27.04 percent increase in labor productivity, while the technological efficiency deteriorates in 14 provinces, with this being most noticeable in Hainan. Labor productivity has fallen falls by 26.53 percent as a consequence. The relative contribution of human capital accumulation also differs substantially between provinces. The standard deviation of labor productivity changes that it causes is 0.1001, which is greater than its average value of 0.0946. Labor productivity in most provinces (26 provinces) benefits from human capital accumulation – it (typically) causes labor productivity in Beijing to increase by 44.18 percent, but has a small negative impact on labor productivity growth in the other four provinces – for example, human capital accumulation caused Hebei's labor productivity to fall by 2.79 percent. The role of capital deepening also shows obvious inter-provincial differences. In all provinces (with the exception of Beijing, where capital deepening has reduced labor productivity by 41.53 percent), capital deepening has promoted labor productivity growth, and this has been particularly apparent in Guizhou and Chongqing, which respectively experienced labor productivity growth of 389.11 percent and 311.78 percent. Technological progress has clearly, without exception, promoted the growth of labor productivity in all provinces, although there are large inter-provincial differences. Beijing and Ningxia have respectively benefited to the greatest and least extent, as attested to by respective labor productivity increases of 287.40 and 38.30 percent.

It should also be noted that the technological progress of all provinces promotes the growth of labor productivity because the sequential DEA has been used to construct the production frontier. If other methods are used to build this frontier, then some provinces will evidence technological regress. However, the authors believe this will only occur in circumstances that huge natural disasters or wars, which appear as extremely rare exceptions to the general tendency of economic development. It is therefore necessary to adopt a production frontier idea that avoids technological regress.

5 Source analysis of the evolution of China's provincial labor productivity gap

5.1 β convergence analysis of labor productivity growth

Upon the basis of multiple decomposition results of labor productivity growth, Spearman rank correlation and β convergence tests are performed on the cumulative labor productivity growth rate and its constituent factors during the period 1997-2016 and are also applied to the 1997 labor productivity level. The results are shown in Table 3 and Figure 3. The results of the rank correlation test and the scatter plot (see Figure 3) show that the growth rate of labor productivity in China's provinces was negatively correlated with the level value in 1997 (at a significance level of 1 percent), which shows that the labor productivity growth rate generally grows faster in relatively underdeveloped than developed provinces. The β convergence test results confirm that the labor productivity of China's provinces experiences absolute β convergence at a significance level of 1 percent.

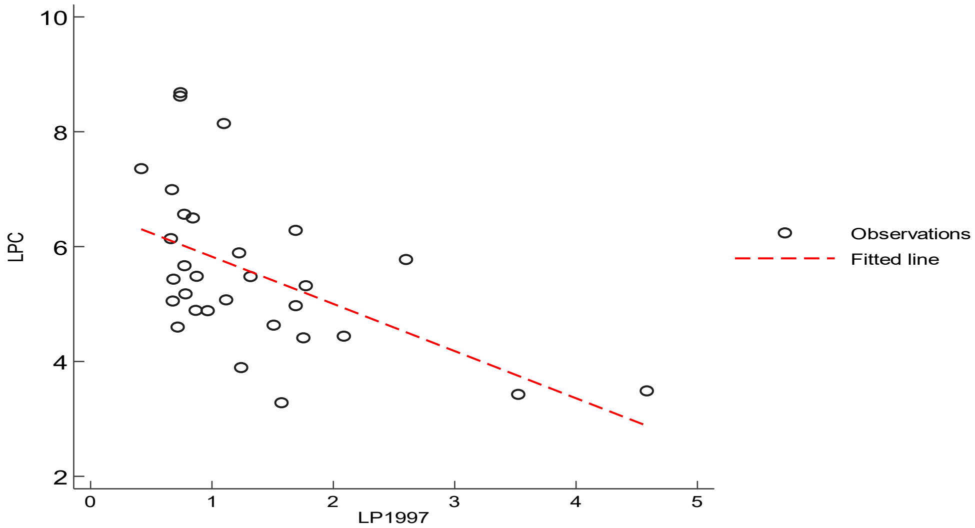


Figure 3: Labor productivity growth of Chinese provinces

Notes:*LP97*、*LPC* represents labor productivity in 1997 and cumulated labor productivity growth during 1997-2016.

Table 3: The results of Spearman rank correlation test and β convergence test

Dependent variable	**β convergence test**			**Spearman rank correlation test**		
	Case 1	**Case 2**	**Case 3**	**Case 1**	**Case 2**	**Case 3**
LPC	-0.8217*** (0.0026)	-0.8217*** (0.0026)	-0.8217*** (0.0026)	-0.5520*** (0.0020)	-0.5520*** (0.0020)	-0.5520*** (0.0020)
EC	0.0130 (0.6590)	-0.0094 (0.7982)	0.0077 (0.7655)	0.0610 (0.7490)	-0.0490 (0.7980)	0.0570 (0.7650)
TC	0.4549*** (0.0000)	0.0827* (0.0928)	0.5159*** (0.0000)	0.7370*** (0.0000)	0.3120* (0.0930)	0.8600*** (0.0000)
KC	-0.8454*** (0.0000)	-0.7939*** (0.0002)	-0.8669*** (0.0000)	-0.8520*** (0.0000)	-0.6240*** (0.0000)	-0.8270*** (0.0000)
HC	0.0477** (0.0174)	0.0988*** (0.0006)	-	0.4310** (0.0170)	0.5920*** (0.0010)	-
TFPC	0.4998*** (0.0000)	0.0657 (0.4946)	0.5416*** (0.0000)	0.4910*** (0.0060)	0.1300 (0.4950)	0.8080*** (0.0060)
KHC	-0.8686*** (0.0000)	-0.7633*** (0.0007)	-	-0.8550*** (0.0000)	-0.5830*** (0.0000)	-

Notes: The authors have calculated all table data with Stata15.0. *P* values in the brackets. ***, **, and * respectively represent the significance levels of 1 percent, 5 percent and 10 percent. Case 1 is this paper's input and output variable settings; Case 2 ignores energy and environmental variables such as those identified by Li et al.(2006);Case 3 ignores human capital variables, such as those identified by Zhu(2014).

So, what is the source of this convergence in labor productivity growth? Factor accumulation, TFP changes or other factors? The results of the β convergence test and rank correlation test based on the double decomposition results of labor productivity growth show that factor accumulation and TFP changes have respectively experienced β convergence and β divergence (see Table 3). To put it differently, during the period 1997-2016, factor accumulation contributed to the narrowing of the gap in the growth of labor productivity in China's provinces, while TFP changes instead widened this gap. Test results based on the quadruple decomposition show that capital deepening experienced significant β convergence and demonstrate technological progress and human capital accumulation both experienced significant β divergence, with the effect of technological progress being especially prominent in this regard. But changes in technological efficiency do not obviously cause β convergence or divergence. When the evolution of China's inter-provincial labor productivity gap during the period 1997-2016 is assessed from the perspective of the trend of growth rate, it becomes apparent that capital deepening has promoted the narrowing of inter-provincial gaps, while technological progress and human capital accumulation (the former in particular) have contributed to its widening. Meanwhile, the role of changes in technological efficiency is not obvious.

5.2 (Counterfactual) dynamic analysis of the distribution of labor productivity

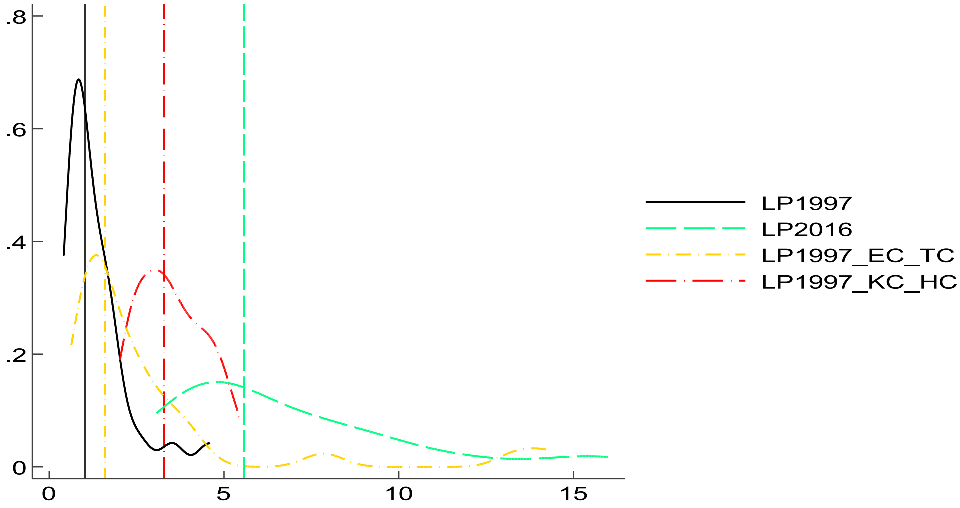
Quah(1993) points out that the β convergence does not necessarily lead to a narrowing of the developmental level gap between different individuals. In order to ascertain if the gap has narrowed, we should analyze their distribution dynamics. In recent years, kernel density map has been widely applied to characterize the distribution dynamics, which has made it possible to explore if the level gap of different variables between different individuals has gradually decreased over time – this approach, it will be noted, resembles testing for the existence of θ convergence. With the intention of exploring the factors that influence labor productivity distribution dynamics, we seek to describe the distribution dynamics of labor productivity across China's provinces by using a Gaussian kernel density map (see Figure 4), and combine it with multimodal (see Table 4) and non-parametric tests (see Table 5) from a perspective of θ convergence.

A counterfactual labor productivity analysis is then conducted with the intention of exploring the impact of changes in technological efficiency, technological progress, capital deepening and human capital accumulation (attention will also focus on their combined effects) on the evolution of the provincial gap in labor productivity level. Equation (7) is a calculation formula of counterfactual labor productivity based on changes in technological efficiency, and the calculation method of other counterfactual labor productivities resembles its. Of them, LP_{2016}^{EC} represents changes in technological efficiency in 2016, LP_{1997} represents actual labor productivity in 1997 and EC represents cumulative technological efficiency changes between 1997 and 2016. It is obvious that differences between LP_{2016}^{EC} and LP_{1997} only originate from the impact of changes in technological efficiency during the analysis period. A comparison of differences between LP_{2016}^{EC} and actual labor productivity in 2016 (LP_{2016}) , enables us to engage across provinces and judge the role of technological efficiency changes in the evolution of labor productivity distribution.

$$LP_{2016}^{EC} = LP_{1997} \times EC \tag{7}$$

5.2.1 A "Polarization" analysis of labor productivity

A number of recent studies in China discuss the "polarization" phenomenon by referring to the unbalanced development of China's regional economy. For example,Li et al. (2006) and Hong (2010) suggest that the degree of regional "polarization" of GDP (per capita) is increasing. It is therefore surprising that existing research rarely engages with this theme of provincial labor productivity. We will now address this oversight by applying the multimodal test.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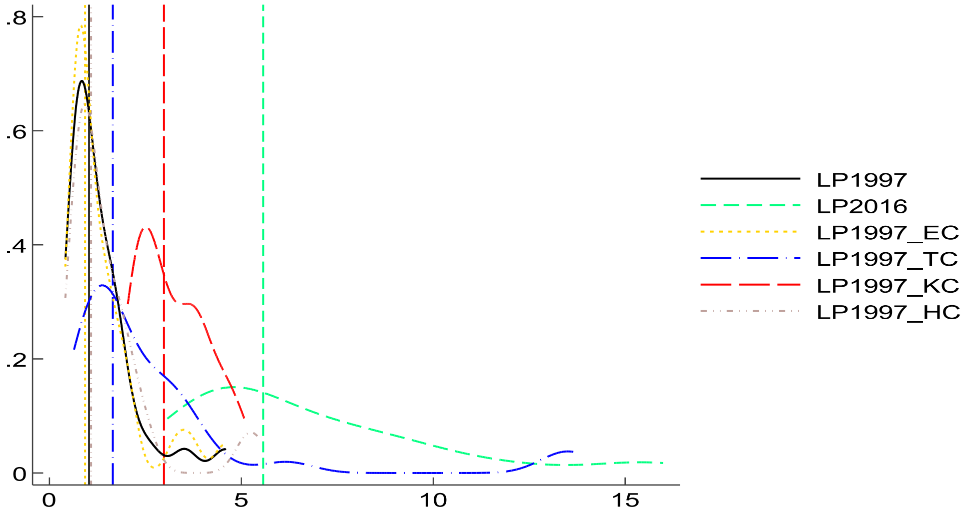
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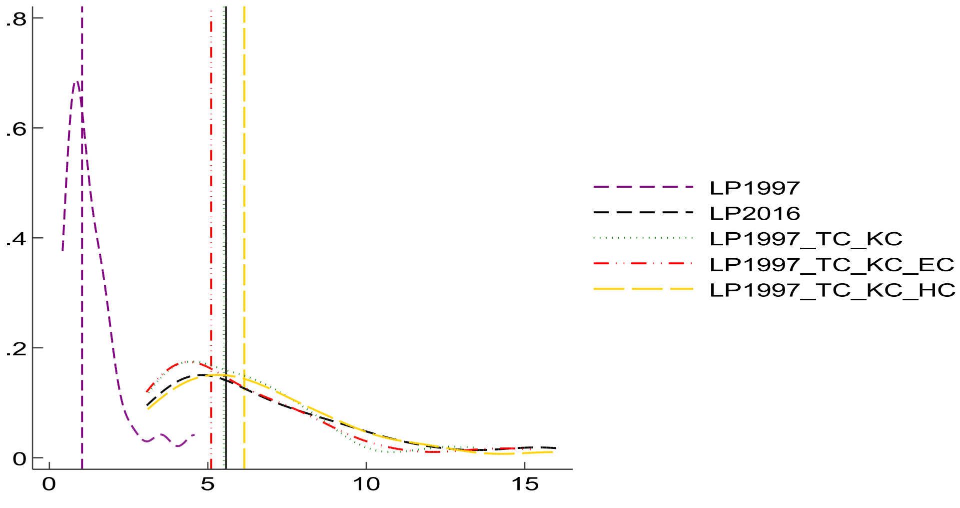
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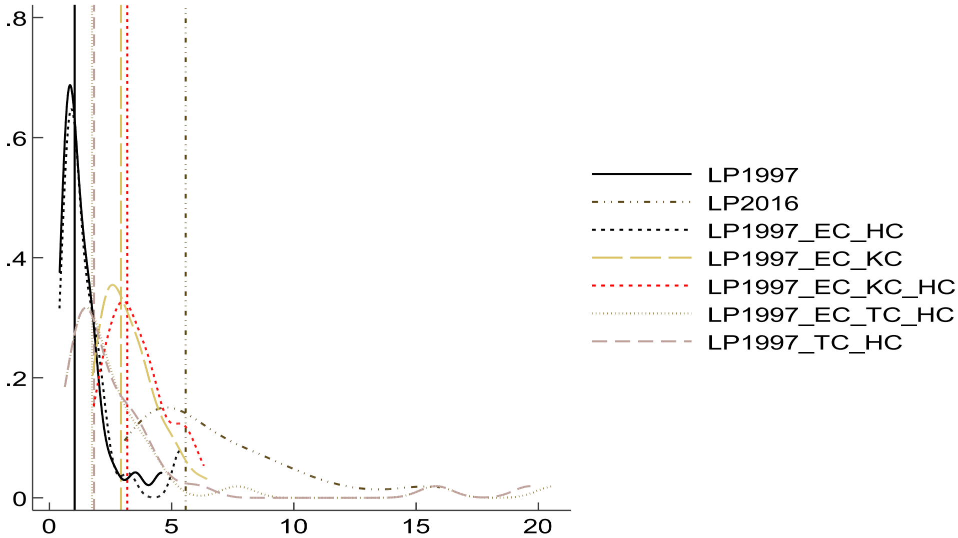

4-D

Figure 4: The result of Gaussian kernel density estimation

Notes: The distribution curves are estimated on the basis of the Gaussian kernel density function with Stata 15.0. The bandwidth is the optimal bandwidth of each series, and the vertical line is the median line.

Table 4: The results of multimodal test

Variable	**Case 1**	**Case 2**	**Case 3**	**Variable**	**Case 1**	**Case 2**	**Case 3**
LP_{1997}	0.0967 (0.6400)	0.0967 (0.6400)	0.0967 (0.6400)	$LP_{2016}^{TFPC\times HC}$	0.1046 (0.4620)	0.1090 (0.3660)	-
LP_{2016}	0.0752 (0.9540)	0.0752 (0.9540)	0.0752 (0.9540)	$LP_{2016}^{EC\times KC}$	0.1128 (0.3520)	0.0806 (0.9300)	0.1181 (0.2680)
LP_{2016}^{EC}	0.1068 (0.4140)	0.0690 (0.9840)	0.0810 (0.8720)	$LP_{2016}^{EC\times HC}$	0.0962 (0.6420)	0.0905 (0.7520)	-
LP_{2016}^{TC}	0.1277 (0.1400)	0.1285 (0.1340)	0.0762 (0.9480)	$LP_{2016}^{EC\times KC\times HC}$	0.1137 (0.3780)	0.0787 (0.7440)	-
LP_{2016}^{KC}	0.1141 (0.4820)	0.1031 (0.4180)	0.1121 (0.5060)	$LP_{2016}^{TC\times KC}$	0.1473* (0.0560)	0.0987 (0.5660)	0.0964 (0.6780)
LP_{2016}^{HC}	0.0910 (0.7420)	0.0892 (0.7320)	-	$LP_{2016}^{TC\times HC}$	0.0793 (0.9200)	0.1131 (0.3120)	-
LP_{2016}^{TFPC}	0.0963 (0.5940)	0.1301 (0.1060)	0.07380 (0.9600)	$LP_{2016}^{TC\times KC\times HC}$	0.1021 (0.5060)	0.0985 (0.5440)	-
$LP_{2016}^{TFPC\times KC}$	0.0799 (0.9060)	0.0908 (0.7440)	-	$LP_{2016}^{KC\times HC}$	0.1115 (0.5160)	0.1189 (0.2160)	-

Notes: The multimodal test uses the ACR model in the Excess Mass Method with R 3.6. The original hypothesis holds that the test variable follows a unimodal distribution, while the alternative hypothesis claims that the test variable follows a multimodal (including bimodal) distribution. The data outside the brackets is the calculated value of excess mass, while the P value is indicated in brackets; * means that the null hypothesis is rejected at the significance level of 10 percent.

The labor productivity distribution curve in Figure 4 shows that the gap between the levels of labor productivity in China's provinces increased significantly during the period 1997-2016. When compared against 1997, it is noticeable that the 2016 labor productivity distribution curve generally shifted to the right and the peak shifted significantly to the lower right, which indicates that the concentration of labor productivity distribution in China's provinces significantly decreased and highlights that the labor productivity level gap significantly expanded. The right-trailing part of the 2016 distribution curve shows small fluctuations, which seems to indicate that provinces with higher levels of labor productivity have a tendency to concentrate. This raises the question of a "clustering" or "polarization" of labor productivity emerged as the gap in labor productivity between China's provinces expanded. The multimodal test results of LP_{2016} in Table 4 show there is no multi-peak (including bi-peak) phenomenon in the distribution of labor productivity in China's provinces, which means that the "polarization" phenomenon identified by macroeconomic research did not occur here. With regard to the "polarizing" effect of labor productivity growth sources and their effect on labor productivity, the other counterfactual labor productivity distributions were not found to be multimodal (including bimodal) in a statistically significant sense and the only exception in this regard was the combination of capital deepening and technological advancement. This meant they did not have a "polarizing" effect on the distribution of inter-provincial labor productivity. In referring to the counterfactual labor productivity distribution that corresponds to the combination of technological advancement and capital deepening, it rejects the unimodal distribution hypothesis at a significance level of only 10 percent, which establishes that their combined effect tends to promote the "polarization" of inter-provincial labor productivity distribution. But this effect is relatively small, and therefore fails to produce the "polarization" of the inter-provincial labor productivity distribution.

5.2.2 The causes of the widening gap in labor productivity level

The nonparametric hypothesis test of unknown distribution, in referring to two functions $f(x)$ and $g(x)$ whose distributions are unknown holds that if $f(x) = g(x)$ for all x, then the two distribution functions are the same, and vice-versa. In examining if the distribution functions of counterfactual labor productivity and real labor productivity are the same, we should seek to ascertain the role of sources of economic growth (or any combination of them) in the evolution of regional economic differences. The combination of Figure 4 and Table 5 makes it possible to draw the following conclusions:

(1)TFP changes, factor accumulation and their constituent factors have all contributed to the growth of labor productivity and the widening gap of the level of inter-provincial labor productivity; however, when considered in isolation they cannot explain the widening gap. Figure 4-A shows that, when compared with the 1997 labor productivity distribution curve, the median lines of the counterfactual labor productivity distribution curve, which are based on TFP changes and factor accumulation, all shifted to the right, with the latter shifting to a much greater extent. While both contribute to the growth of labor productivity, the latter has a stronger effect. Their peaks obviously move to the lower right, and this shows that TFP changes and factor accumulation both promoted the widening of the gap in labor productivity between China's provinces. However, both of these counterfactual labor productivity distribution curves and their peaks are clearly to the left of the actual situation in 2016, Furthermore, the results of the non-parametric hypothesis test of the same distribution in Table 5 reject the original hypothesis at a significance level of at least 1 percent, which shows that unilateral TFP changes or factor accumulation are not sufficient to explain the evolution of the gaps of labor productivity between China's provinces. With regard to the constituent factors of TFP changes and factor accumulation, the four counterfactual labor productivity distribution curves in Figure 4-B are obviously different from the actual situation in 2016, and their peaks are all below the actual situation in 1997; the downward movement of the distribution curve that corresponds to capital deepening and technological progress is very obvious and is especially pronounced in the latter; meanwhile, the distribution curve and median line that correspond to changes in technological efficiency and human capital accumulation almost coincide with the actual situation in 1997, which indicates that all of them promote the widening gap; technological progress is foremost in this respect, capital deepening has a secondary role and both technological efficiency changes and human capital accumulation have small effects. In relation to their impact on the widening of the inter-provincial labor productivity gap, the results of the non-parametric hypothesis test in Table 5 show the same distribution null hypotheses between these four distribution curves and the accurate curve in 2016 were rejected at a one percent significance level. This indicates that they are unilaterally insufficient to explain the widening of the gap in the level of inter-provincial labor productivity.

(2)The combined effect of capital deepening and technological progress is the root cause that contributes to the widening of the gap in labor productivity levels between China's provinces. Figure 4-C shows that the three corresponding counterfactual labor productivity distribution curves almost overlap with the actual 2016 curve. This applies both under the combined effect of capital deepening and technological advancement, and also extends to their combined effect with technological efficiency changes or human capital accumulation. The results of the non-parametric hypothesis test in Table 5 show that, even at a significance level of 10 percent, the original hypotheses are not rejected. This indicates these related combinations can better explain the widening of the gap at the level of inter-provincial labor productivity. Among them, the median line under the combination of technological progress and capital deepening almost coincides with the actual situation in 2016, and the absolute value of the statistic Tn under this combination is much lower than the other two cases (see Table 5). This shows that the combined effect of capital deepening and technological progress offers the strongest explanation for the widening of the gap at the level of inter-provincial labor productivity. In addition, with regard to any other combination of growth sources, their corresponding counterfactual labor productivity distribution curves (peaks) are clearly located on the left (upper left) of the real situation in 2016 (see Figure 4-D), while all the null hypotheses are rejected at a significance level of at least one percent (see Table 5). This shows that these economic growth source combinations do not sufficiently explain the widening of the gap at the level of inter-provincial labor productivity. These observations clearly demonstrate that the combined effect of technological progress and capital deepening is the root cause that underpins the widening of the gap in the level of China's provincial labor productivity during the period 1997-2016.

Table 5: The results of non-parametric test

Distribution test	**Case 1**	**Case 2**	**Case 3**
$f(LP_{2016}) vs. g(LP_{1997})$	17.8301*** (0.0000)	17.8301*** (0.0000)	17.8301*** (0.0000)
$f(LP_{2016}) vs. g(LP_{1997} \times EC)$	16.0500*** (0.0000)	17.1469*** (0.0000)	17.1586*** (0.0000)
$f(LP_{2016}) vs. g(LP_{1997} \times EC \times TC)$	13.8470*** (0.0000)	15.3494*** (0.0000)	13.4462*** (0.0000)
$f(LP_{2016}) vs. g(LP_{1997} \times EC \times KC)$	7.3905*** (0.0010)	3.4397*** (0.0000)	5.9187*** (0.0000)
$f(LP_{2016}) vs. g(LP_{1997} \times EC \times HC)$	15.2093*** (0.0000)	16.9660*** (0.0000)	-
$f(LP_{2016}) vs. g(LP_{1997} \times EC \times TC \times KC)$	-0.8786 (0.9750)	0.0705 (0.7870)	-
$f(LP_{2016}) vs. g(LP_{1997} \times EC \times TC \times HC)$	11.3163*** (0.0000)	12.3671*** (0.0000)	-
$f(LP_{2016}) vs. g(LP_{1997} \times EC \times KC \times HC)$	5.1400*** (0.0010)	0.8430** (0.0476)	-
$f(LP_{2016}) vs. g(LP_{1997} \times TC)$	12.8705*** (0.0000)	16.1250*** (0.0000)	11.8764*** (0.0000)
$f(LP_{2016}) vs. g(LP_{1997} \times TC \times KC)$	-0.3584 (0.8910)	-0.4057 (0.3033)	-1.2106 (0.7394)
$f(LP_{2016}) vs. g(LP_{1997} \times TC \times HC)$	11.3839*** (0.0000)	13.6848*** (0.0000)	-
$f(LP_{2016}) vs. g(LP_{1997} \times TC \times KC \times HC)$	-1.3737 (0.7770)	0.2539 (0.9048)	-
$f(LP_{2016}) vs. g(LP_{1997} \times KC)$	7.1968*** (0.0010)	3.0505*** (0.0000)	5.8632*** (0.0000)
$f(LP_{2016}) vs. g(LP_{1997} \times KC \times HC)$	5.8416*** (0.0010)	0.9981** (0.0426)	-
$f(LP_{2016}) vs. g(LP_{1997} \times HC)$	14.3844*** (0.0000)	13.6890*** (0.0000)	-

Notes: The authors have calculated all table data with R3.6. The non-parametric test model used here is proposed by Li et al. (2009) which tests for whether two unknown distributions are the same. The data outside of brackets are the *Tn* statistic, and the p value in the brackets. *** and ** denote that the null hypothesis are rejected at the significance level of 1 and 5 percent respectively.

5.3 Robustness analysis

This shows that the widening of the gap in the level of China's inter-provincial labor productivity during the period 1997-2016 can be attributed to the joint predominance of capital deepening and technological progress. This establishes that TFP changes or factor accumulation can not be applied in isolation to explain the evolution of the gap. This broadly resembles the Zhu's (2014) conclusion (although there are large differences in other respects) and almost completely contradicts the conclusion of Li et al. (2006).

Output variables introduce energy and environmental factors into the analysis, but do not include human capital (Case 3); input variables, meanwhile, consider human capital but do not introduce energy and environmental factors (Case 2; in contrast, this paper simultaneously introduces energy, environment, and human capital variables (Case 1). This raises the question of if the aforementioned divergence of results can be attributed to different input and output variable settings rather than the selection of different analytical models. We therefore apply same exercise under our analysis framework to Cases 2 and 3 (the results are shown in Tables 3-5 and Appendix Tables A2-A3) to test the robustness of the aforementioned research conclusions. The results show that the qualitative conclusions in the three cases are highly consistent, which confirms the paper's conclusions are very robust.

(1)The accounting results of the sources of economic growth (see Appendix Tables A2-A3) show that their order of magnitude is the same – this applies whether it is the provincial average, the standard deviation or an instance in which the relative contributions of the sources of growth differs across the three cases differ. Ignoring the relative contribution of energy and environmental variables will overestimate the relative contribution of factor accumulation and underestimate that of TFP changes, while ignoring human capital will lead to opposite results. In addition,there are significant provincial difference of technology efficiencies in case 2 and 3 too(see Appendix Figures A1-A2).

(2)The results of the convergence test and rank correlation test(see Table 3) show that the conclusions are also consistent across the three cases. During the process when the increased labor productivity of China's provinces tends to converge, capital deepening has a significant promotional effect; meanwhile, technological progress and the accumulation of human capital have a significant inhibitory effect and the role of technological efficiency changes is not obvious.

(3)The results of the analysis of the dynamic distribution (see Tables 4-5 and Appendix Figures A3-A4) show slight differences in the results obtained from the three cases. However, none of them are sufficient to overturn conclusions reached at an earlier point in this paper. The multimodal test results of Cases 2 and 3 and the distribution of inter-provincial labor productivity under the combination of capital deepening and technological progress show a clear unimodal distribution. While Case 1 rejects the original hypothesis of unimodal distribution, its significance level is only 10 percent, and it therefore has little effect on the conclusion that relates to the widening of labor productivity gaps between provinces. In the same non-parametric test of unobserved distribution, the conclusions of Cases 1 and 3 are the same, while Case 2 is slightly different. When Case 2 is engaged with the intention of explaining the evolution of the level of labor productivity in China's provinces, it becomes apparent that the combined effect of technological progress and capital deepening is slightly lower than the effect that is produced when both are combined with changes in technological efficiency (or human capital accumulation) – this much can be inferred from the absolute value of the statistic Tn. However, it can still be concluded that the combined effect of capital deepening and technological progress is the root cause that underpins the evolution of the gap in the level of labor productivity in China's provinces. Any engagement that ignores or overlooks their combined effect will not be able to sufficiently explain the gap's evolution.

6 Conclusions

In drawing on the perspective of economic growth accounting, this paper seeks to establish a systematic analysis framework for sources of the regional economic gap that applies analytical methods that include DEA-based green economic growth accounting analysis, the economic growth convergence test, the counterfactual labor productivity analysis, the multi-peak test, and non-parametric test of the same distribution. In engaging with the growth rate and the values of the level of labor productivity, it re-examines the sources and evolution of China's inter-provincial economic gap during the period 1997-2016. It offers four main conclusions:

(1)Due to the combined effect of factor accumulation (mainly capital deepening) and TFP changes (mainly technological progress), labor productivity in all of China's provinces has greatly improved. In addition, extensive economic growth has been clearly evidenced, to the point of being obvious.

(2)China's inter-provincial labor productivity growth has experienced significant β convergence – capital deepening has been dominant in this process, and technological progress and human capital accumulation have significantly inhibited it. The role of technological efficiency changes, meanwhile, has remained very vague.

(3)The gap between levels of labor productivity in China's provinces has increased significantly, but there has been no "polarization" phenomenon. Capital deepening and technological advancement are the fundamental factors that drive the evolution of this gap, while the accumulation of human capital and changes in technological efficiency have contributed small promotional effects.

(4)Different choices of input and output variables will affect the estimated value of relevant parameters in the analysis, but will not change the conclusions of qualitative analysis. Specifically,it will overestimate the relative contribution of factor accumulation and underestimate that of TFP changes if energy and environmental factors are not considered in growth accounting analysis;on the other hand,it will lead to opposite biased results if human capital is ignored.

These conclusions indicate that the extensive economic growth mode that adopts capital deepening as its main feature is well-placed to explain the economic development of China's provinces. In recent years, it has become apparent that this enables 'backward' provinces to "catch up" with the growth rate of relatively developed counterpart provinces. But this has not promoted the narrowing of the gap at the level of inter-provincial labor productivity, and has instead contributed to its widening, and this tendency is also shown in technological progress. Policy actors seeking to achieve the balanced development of China's regional economy cannot therefore rely solely on innovation in the expectation this will improve the technological level of "backward" regions. It is important for them to continue to promote factor accumulation and improvements in technological efficiency. During the innovation-driven high-quality development stage, the making of scientific decisions and the implementation of a factor accumulation and TFP advancement strategy focused on 'backward' areas both become very important. Due to research purpose limitations, this paper cannot discuss this issue in depth, and nor can it specifically analyze the various factors that influence sources of economic growth. Future research should seek to engage across a wider period of time and incorporate more undesirable output variables, such as COD and CO_2 into the empirical analysis. These are preconditions for future research that seeks to supplement and refine the current paper.

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Appendix tables

Table A1: The Data used in this paper

Year	Province	GDP	Physical capital	Labor	Human capital	Energy	SO_2
1997	Beijing	2328.2898	7606.5215	660.8000	5.5442	3833.0000	21.0827
1997	Tianjin	1277.5454	3448.3689	491.6000	4.6841	2459.0000	23.4943
1997	Hebei	3814.0391	6965.5554	3415.0000	3.8536	9033.0000	100.8922
1997	Shanxi	1430.7083	3757.6737	1483.2000	4.0742	6983.0000	68.9285
1997	Neimenggu	1153.3369	2412.5490	1050.3000	3.7472	3374.0000	53.1603
1997	Liaoning	3658.8919	6864.1142	2063.3000	4.3231	9474.0000	83.7627
1997	Jilin	1513.8963	3083.3415	1237.3000	4.2704	4333.0000	19.3184
1997	Heilongjiang	2501.7237	5274.0593	1658.6000	4.2054	6435.0000	22.4417
1997	Shanghai	3529.8587	9539.7093	770.2000	4.9596	4759.0000	40.0947
1997	Jiangsu	6328.3149	12015.5293	3745.5000	3.6760	7991.0000	99.8173
1997	Zhejiang	4563.9824	8836.0730	2700.3000	3.6393	5069.0000	41.0868
1997	Anhui	2267.9277	4464.2895	3321.7000	3.4229	4405.0000	33.2287
1997	Fujian	2828.4877	4206.3073	1613.4000	3.5676	2536.0000	11.7244
1997	Jiangxi	1606.4386	2815.0417	2077.7000	3.6498	2132.0000	21.6527
1997	Shandong	6201.9224	11469.1968	4707.0000	3.4884	9154.0000	149.6739
1997	Henan	3923.5549	7052.5024	5017.0000	3.7534	6711.0000	68.0624
1997	Hubei	2788.5960	5137.3051	3311.2000	3.7799	6109.0000	38.6835
1997	Hunan	2770.2890	4455.7835	3590.7000	3.7479	4808.0000	46.8257
1997	Guangdong	7896.8316	9726.5885	3784.3000	4.0462	7953.0000	47.6337
1997	Guangxi	1622.6834	3618.6518	2452.4000	3.4730	2605.0000	49.8182
1997	Hainan	410.5597	1141.6749	330.9000	3.8936	390.3000	1.6891
1997	Chongqing	1266.7928	2482.1859	1715.4000	3.3982	2030.1300	71.4300
1997	Sichuan	3095.9934	5621.2548	4617.6000	3.4096	6628.0000	64.1198
1997	Guizhou	804.8512	2278.2827	1927.1000	3.0626	3960.0000	60.9250
1997	Yunnan	1612.9437	3559.9627	2247.6000	3.0718	3428.9800	27.0427
1997	Shanxi-W	1327.4793	3522.2106	1792.0000	3.7439	3111.0000	54.8012
1997	Gansu	802.6739	2818.4710	1185.9000	3.2429	2581.0000	35.7872
1997	Qinghai	205.6817	3070.0279	235.4000	2.9447	706.8000	2.5290
1997	Ningxia	225.5362	3158.6047	260.4000	3.3710	805.0000	18.5703
1997	Xinjiang	1086.5056	4045.2555	690.7000	3.9229	3230.0000	16.0358
2016	Beijing	14734.1968	48820.1056	1220.1000	8.9219	4215.2883	3.3200
2016	Tianjin	13545.6168	55399.0019	902.4200	6.2589	5962.0437	7.0600
2016	Hebei	23933.8337	92506.3640	4223.9500	5.1293	21256.5173	78.9400
2016	Shanxi	8991.1716	42714.7401	1908.2100	5.3996	12692.2521	68.6400
2016	Neimenggu	13180.9124	72956.2965	1474.0000	5.1258	12508.0318	62.5700
2016	Liaoning	21707.1013	79812.2172	2301.1558	5.3282	15885.5278	50.7700

2016	Jilin	10825.2824	54686.4849	1501.7000	5.0215	5521.3804	18.8100
2016	Heilongjiang	14516.4848	50164.6358	2077.3000	5.1220	10578.1684	33.8200
2016	Shanghai	21825.8645	63327.3119	1365.2400	7.2122	9498.3732	7.4200
2016	Jiangsu	50491.7608	151957.3301	4756.2200	5.5208	20595.7162	57.0100
2016	Zhejiang	31596.0574	93696.0729	3760.0000	5.4218	13738.3131	26.8400
2016	Anhui	16181.2137	52950.3604	4361.6000	4.4884	8335.3571	28.1600
2016	Fujian	21632.1737	77249.0737	2797.0300	4.9653	9406.1081	18.9300
2016	Jiangxi	11558.2014	29626.7209	2637.6000	4.7422	5411.6304	27.6900
2016	Shandong	48003.5923	160048.3024	6649.7000	5.0117	26933.3313	113.4500
2016	Henan	27235.2665	139681.1606	6726.3906	4.8857	15397.3745	41.3600
2016	Hubei	19884.0061	74326.7770	3633.0000	4.9980	10400.4845	28.5600
2016	Hunan	19853.8523	67882.2027	3920.4100	5.0586	9903.7049	34.6800
2016	Guangdong	58191.6971	132173.3704	6279.2183	5.4722	23078.6176	35.3700
2016	Guangxi	11541.5810	68491.7163	2841.0000	4.7904	6406.8160	20.1100
2016	Hainan	2696.6621	11276.5706	558.1400	5.0000	1332.8180	1.7000
2016	Chongqing	10933.4610	39536.5276	1717.5200	4.8956	5745.7495	28.8300
2016	Sichuan	22785.9952	68270.5057	4859.9972	4.4797	13989.0537	48.8300
2016	Guizhou	6096.1680	30352.8492	1983.7200	3.9769	5499.4600	64.7100
2016	Yunnan	9898.6270	54877.8321	2998.8900	4.1013	6968.9420	52.6200
2016	Shanxi-W	11466.4440	53729.9185	1783.0000	5.1988	6770.8433	31.8000
2016	Gansu	5296.9801	21260.8619	1548.7400	4.5165	4884.4042	27.2000
2016	Qinghai	1553.7501	14760.3796	324.2800	4.5958	2373.4594	11.3700
2016	Ningxia	1563.7177	16838.6287	369.2000	4.9351	2657.1566	23.6900
2016	Xinjiang	6520.9110	38642.3989	1263.1100	5.2513	9791.0017	48.0700

Notes: The authors have collected all table data from the *China Economic Network*, the *China Statistical Yearbook*, the *China Environmental Statistics Yearbook*, the *China Energy Statistics Yearbook* and the *Chongqing Statistical Yearbook* and calculated by the authors. The GDP and physical capital stock data are adjusted by the GDP deflator and the fixed asset investment price index respectively, and the base period is 2000. The units of all variables are the same as Table 1.

Table A2: The results of economic growth accounting ignoring environmental and energy factors

Province	***LPC***	***TFPC***			***KHC***		
		Total	***EC***	***TC***	***Total***	***KC***	***HC***
Beijing	3.4274	3.8989	1.0000	3.8989	0.8791	0.8791	—
Tianjin	5.7760	3.4001	1.1915	2.8537	1.6988	1.6988	—
Hebei	5.0734	1.5324	0.8850	1.7315	3.3107	3.3107	—
Shanxi	4.8847	1.4453	0.9738	1.4841	3.3797	3.3797	—
Neimenggu	8.1434	1.7742	0.9499	1.8677	4.5899	4.5899	—
Liaoning	5.3195	1.7923	0.9410	1.9046	2.9679	2.9679	—
Jilin	5.8916	1.8737	0.8967	2.0896	3.1444	3.1444	—
Heilongjiang	4.6330	1.6652	0.8843	1.8831	2.7823	2.7823	—
Shanghai	3.4883	3.2374	1.0000	3.2374	1.0775	1.0775	—
Jiangsu	6.2832	2.4756	1.1478	2.1569	2.5380	2.5380	—
Zhejiang	4.9718	2.2436	0.9810	2.2872	2.2160	2.2160	—
Anhui	5.4337	1.7632	1.0885	1.6198	3.0818	3.0818	—
Fujian	4.4115	1.7097	0.7836	2.1819	2.5803	2.5803	—
Jiangxi	5.6676	1.8566	1.1873	1.5637	3.0527	3.0527	—
Shandong	5.4789	1.9277	1.0611	1.8167	2.8421	2.8421	—
Henan	5.1774	1.6470	0.8752	1.8818	3.1436	3.1436	—
Hubei	6.4989	1.8987	0.9885	1.9207	3.4228	3.4228	—
Hunan	6.5640	1.7029	0.9664	1.7622	3.8545	3.8545	—
Guangdong	4.4411	2.1772	1.0000	2.1772	2.0398	2.0398	—
Guangxi	6.1398	1.7966	0.9424	1.9064	3.4175	3.4175	—
Hainan	3.8941	1.9595	0.7347	2.6671	1.9872	1.9872	—
Chongqing	8.6202	1.9916	1.1156	1.7852	4.3282	4.3282	—
Sichuan	6.9928	1.7938	1.0769	1.6657	3.8982	3.8982	—
Guizhou	7.3581	1.5200	0.9899	1.5355	4.8408	4.8408	—
Yunnan	4.5995	1.3889	0.8314	1.6705	3.3118	3.3118	—
Shanxi-W	8.6814	2.0334	1.0782	1.8859	4.2693	4.2693	—
Gansu	5.0531	1.5835	1.0313	1.5355	3.1911	3.1911	—
Qinghai	5.4837	1.3485	0.7721	1.7465	4.0665	4.0665	—
Ningxia	4.8901	1.3346	0.9663	1.3812	3.6642	3.6642	—
Xinjiang	3.2819	1.2736	0.7323	1.7392	2.5768	2.5768	—
Mean	5.5520	1.9349	0.9691	1.9946	3.0718	3.0718	—
S.D.	1.4034	0.6070	0.1229	0.5429	0.9491	0.9491	—

Notes: The authors have calculated all table data with MaxDEA. This is the accounting results ignoring energy and environmental factors corresponding to Li et al.(2006) .*LPC* represents cumulative change of labor productivity growth, and *EC, TC, KC, HC, TFPC*, and *KHC* represent cumulative labor productivity changes caused by changes in technological efficiency, technological progress, capital deepening, human capital accumulation, TFP changes, and factor accumulation, respectively. Mean and S.D. are the means and standard deviations.

Table A3: The results of economic growth accounting ignoring human capital

Province	***LPC***	***TFPC***			***KHC***		
		Total	***EC***	***TC***	***Total***	***KC***	***HC***
Beijing	3.4274	1.5301	0.9722	1.5739	2.2399	1.2278	1.8243
Tianjin	5.7760	2.2245	1.2704	1.7510	2.5966	2.4612	1.0550
Hebei	5.0734	1.2735	0.9187	1.3863	3.9838	3.7976	1.0490
Shanxi	4.8847	1.4614	1.0607	1.3778	3.3424	2.8354	1.1788
Neimenggu	8.1434	1.9897	1.2371	1.6083	4.0928	3.5847	1.1418
Liaoning	5.3195	1.6744	1.0617	1.5770	3.1770	2.8396	1.1188
Jilin	5.8916	1.6414	1.0501	1.5631	3.5893	3.4045	1.0543
Heilongjiang	4.6330	1.5941	1.1032	1.4450	2.9064	2.6299	1.1051
Shanghai	3.4883	1.7623	1.0000	1.7623	1.9793	1.3902	1.4238
Jiangsu	6.2832	1.7618	1.1387	1.5472	3.5664	3.0672	1.1628
Zhejiang	4.9718	1.5150	1.0375	1.4602	3.2817	2.5853	1.2694
Anhui	5.4337	1.2177	1.0364	1.1750	4.4624	4.2865	1.0410
Fujian	4.4115	1.2533	0.8332	1.5042	3.5201	2.8214	1.2476
Jiangxi	5.6676	1.2943	1.1416	1.1338	4.3790	3.9962	1.0958
Shandong	5.4789	1.5434	1.0707	1.4415	3.5498	2.8177	1.2598
Henan	5.1774	0.9449	0.6815	1.3864	5.4795	4.8678	1.1257
Hubei	6.4989	1.2917	0.9400	1.3741	5.0313	4.3302	1.1619
Hunan	6.5640	1.0966	0.8499	1.2903	5.9858	5.1185	1.1694
Guangdong	4.4411	1.3541	1.0000	1.3541	3.2797	2.7127	1.2090
Guangxi	6.1398	1.1501	0.7949	1.4469	5.3383	4.8642	1.0975
Hainan	3.8941	1.4105	0.9982	1.4130	2.7608	2.3820	1.1590
Chongqing	8.6202	1.5771	1.1092	1.4218	5.4658	4.6115	1.1853
Sichuan	6.9928	1.3416	1.0769	1.2458	5.2121	4.7550	1.0961
Guizhou	7.3581	1.4181	1.0481	1.3531	5.1887	4.8222	1.0760
Yunnan	4.5995	1.1126	0.7932	1.4026	4.1341	3.5256	1.1726
Shanxi-W	8.6814	1.9201	1.2774	1.5031	4.5213	3.4110	1.3255
Gansu	5.0531	1.7374	1.3943	1.2461	2.9084	2.5438	1.1433
Qinghai	5.4837	3.0480	1.3509	2.2563	1.7991	1.3457	1.3369
Ningxia	4.8901	2.7512	1.3048	2.1086	1.7774	1.3884	1.2802
Xinjiang	3.2819	1.3506	0.8256	1.6359	2.4300	2.0213	1.2022
Mean	5.5520	1.5747	1.0459	1.4915	3.7327	3.2148	1.1923
S.D.	1.4034	0.4588	0.1742	0.2397	1.1859	1.1520	0.1511

Notes: The authors have calculated all table data with MaxDEA. This is the results ignoring human capital corresponding to Zhu(2014);*LPC* represents cumulative change of labor productivity growth, and *EC, TC, KC, HC, TFPC,* and *KHC* represent cumulative labor productivity changes caused by changes in technological efficiency, technological progress, capital deepening, human capital accumulation, TFP changes, and factor accumulation, respectively. Mean and S.D. are the means and standard deviations.

Appendix Figures

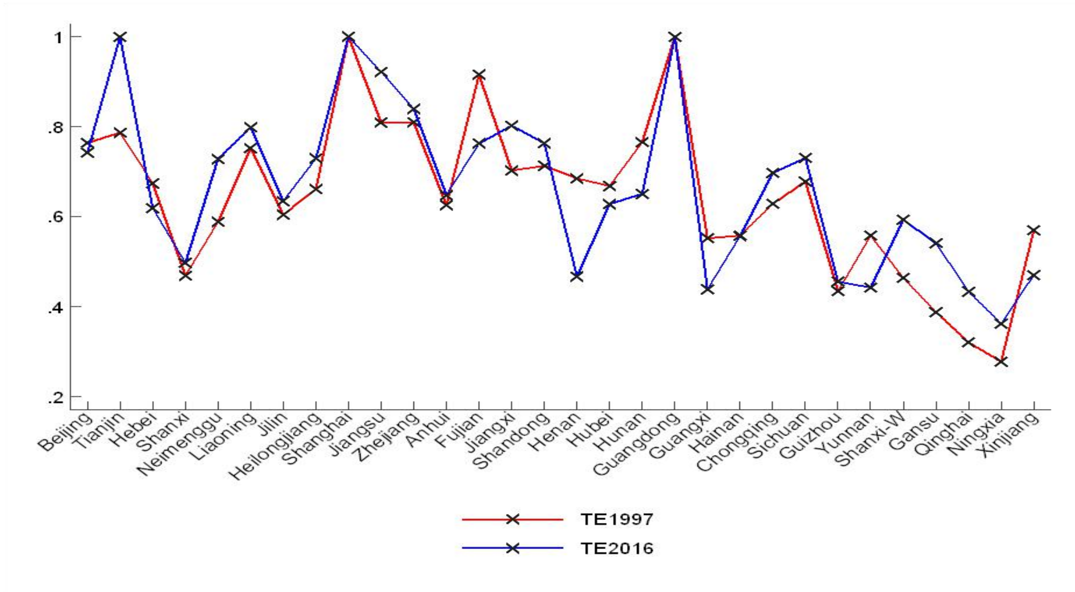


Figure A1: Technology efficiencies of Case 2

Notes: The authors have calculated all figure data ignoring energy and environmental factors with MaxDEA.

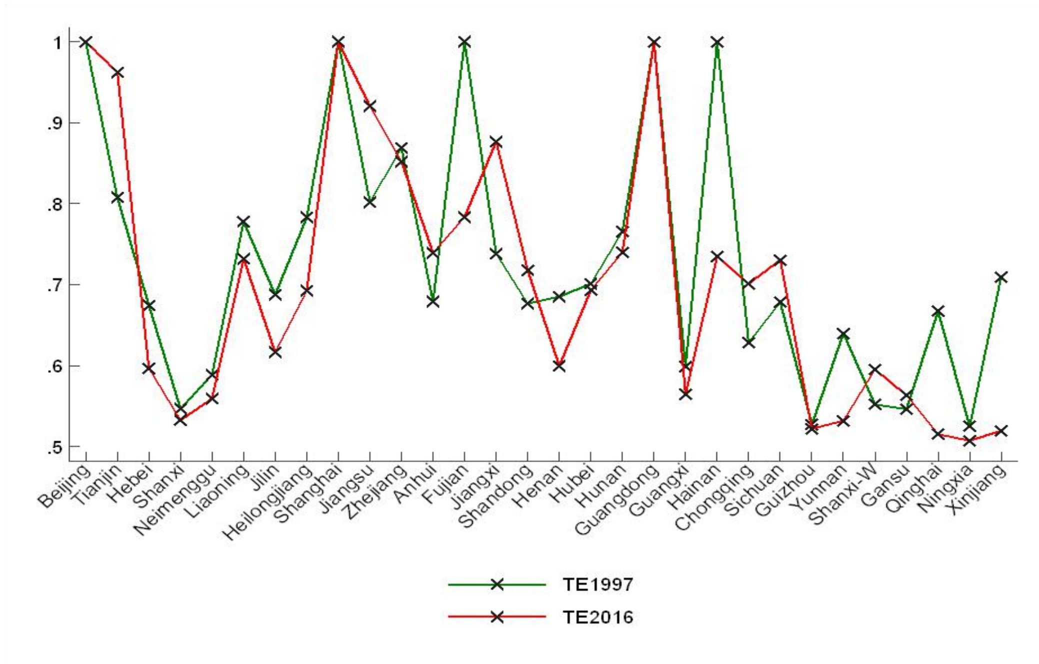
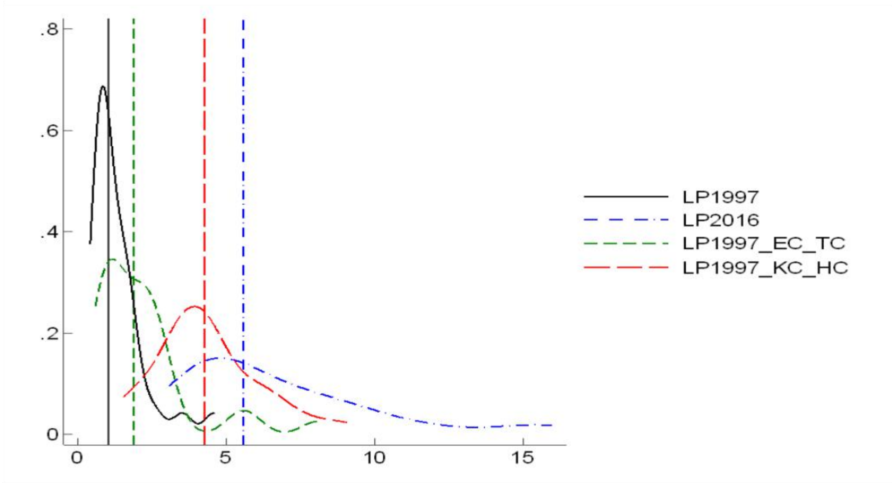


Figure A2: Technology efficiencies of Case 3

Notes: The authors have calculated all figure data ignoring human capital with MaxDEA.



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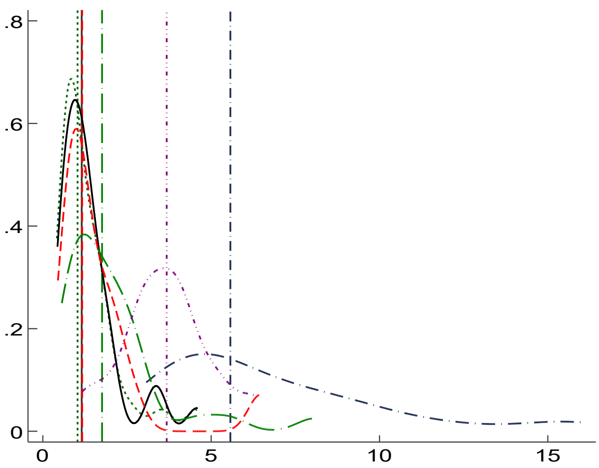
LP1997_KC_HC

A3-A



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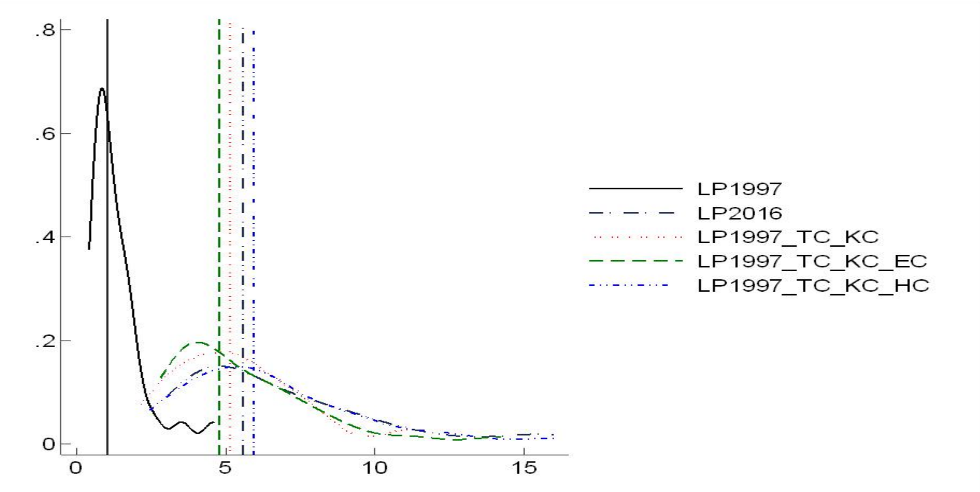
LP1997_EC
LP1997_TC
LP1997_KC
LP1997_HC

A3-B



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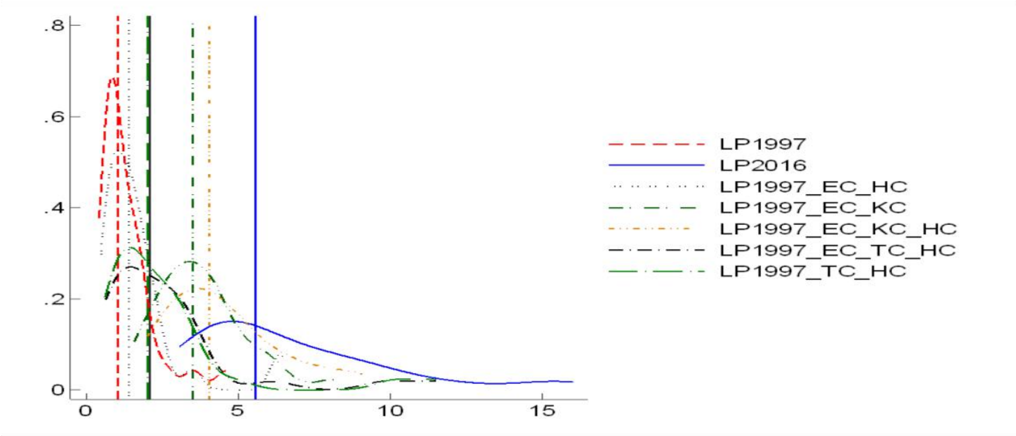
LP1997
LP2016
LP1997_TC_KC
LP1997_TC_KC_EC
LP1997_TC_KC_HC

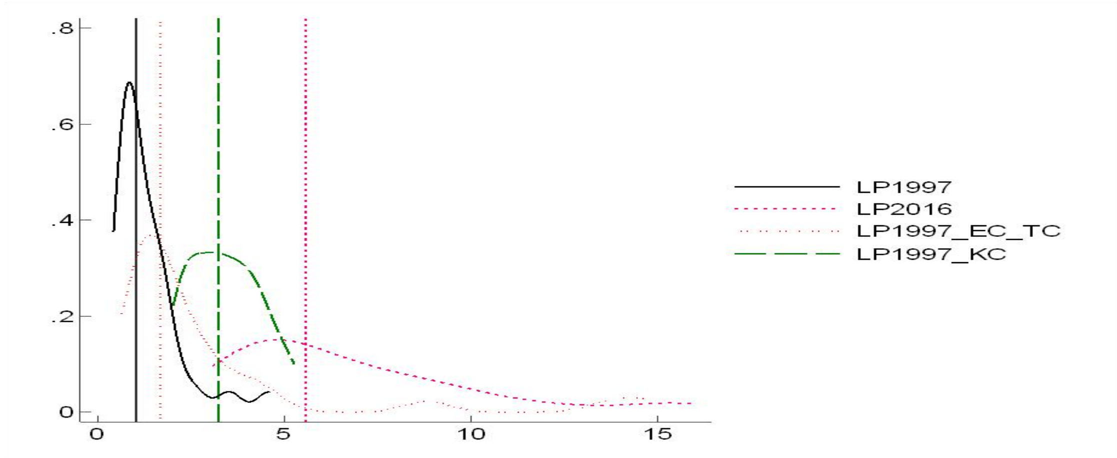
A3-C



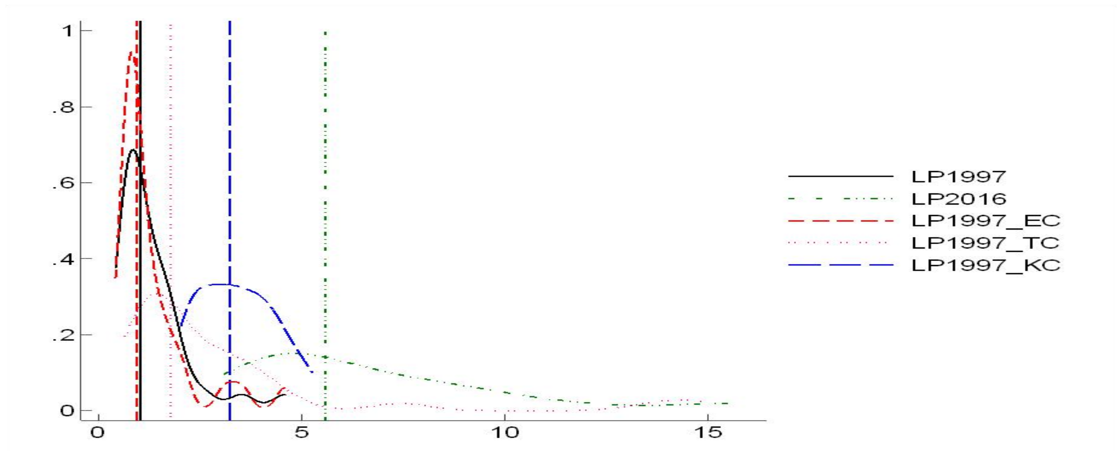
A3-D

Figure A3: The Gaussian kernel density estimation of Case 2

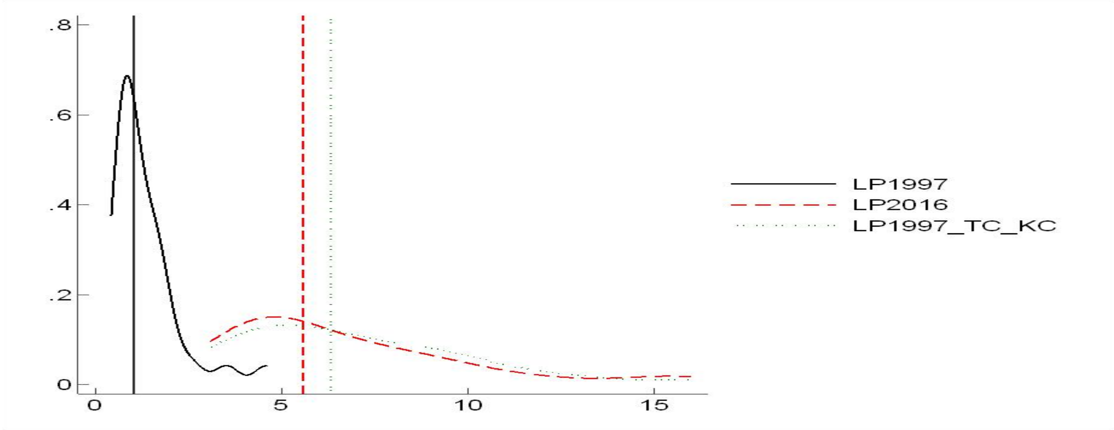
Notes: The distribution curves are estimated on the basis of the Gaussian kernel density function ignoring energy and environmental factors with Stata 15.0. The bandwidth is the optimal bandwidth of each series, and the vertical line is the median line.



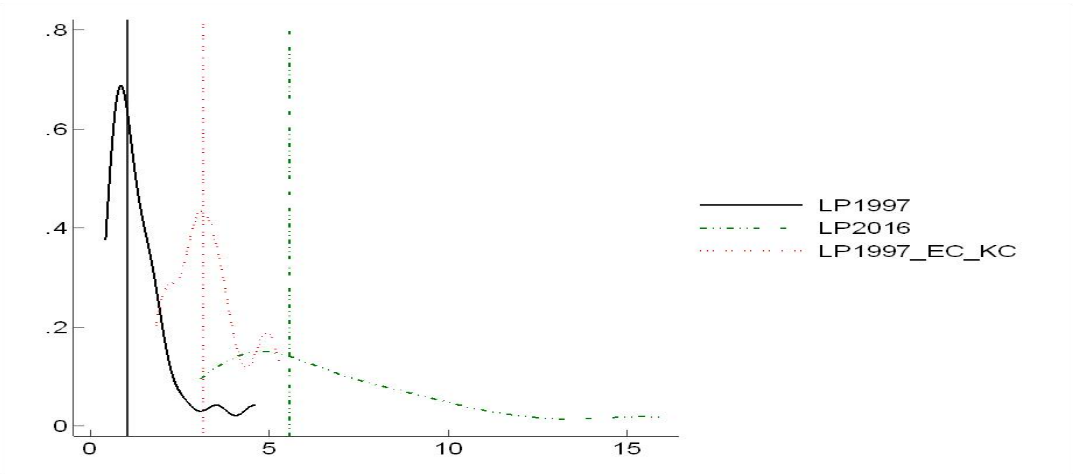
A4-A



A4-B



A4-C



A4-D

Figure A4: The Gaussian kernel density estimation of Case 3

Notes: The distribution curves are estimated on the basis of the Gaussian kernel density function ignoring human capital with Stata 15.0. The bandwidth is the optimal bandwidth of each series, and the vertical line is the median line.