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Green total factor productivity: A re-examination of quality of growth for provinces in China

Fan Xia, Jintao Xu*

National School of Development, Peking University, 100871, China

ABSTRACT

In this paper we try to assess the quality of growth for provinces in China over the period of 1997–2015. To do so we calculate a set of Green total factor productivity (or GTFP) indexes by incorporating environmental performance variables at the provincial level. A nonparametric approach (Directional Distance Function a la Chung et al., 1997) is adopted in the estimation. Furthermore, we apply bootstrapping method to correct estimation bias and obtain statistical property of the estimated indexes. The GTFP indexes estimated here demonstrate very different trends from the GDP growth rateand standard TFP indexes ignoring environmental outcomes. For the period of interests, when annual GDP growth rate was very high, no steady growth was found in TFP and GTFP, by contrast. The rankings of provinces differ significantly across measures of GDP growth, TFP and GTFP. In addition, our estimates of GTFP trends are also significantly different from findings by other papers of GTFP estimation (Hu et al., 2008; Wang et al., 2010) without bootstrapping procedure.

1. Introduction

China has enjoyed 9.5% annual growth in gross domestic products since her reform and opening up to the world in late 1970s. Per capita GDP also grew at an annual rate of 8.5% (World Bank Data, 2020). However, this phenomenal economic performance was accompanied by severe environmental damage and resource degradation. Energy consumption grew on par with GDP. During the five years of 2003–2007, average annual energy use per capita growth rate was 11% (World Bank Data, 2020). Most regions suffered serious environmental quality aggravation resulting from uncontrolled pollution. To stop the trend of worsening environmental quality, in the thirteenth five year plan for national economic and social development (2016–2020), the government set up ambitious targets stipulating to reduce energy consumption per unit GDP by 15%, to reduce air borne $PM_{2.5}$ concentration by 18% and to reduce the levels of major pollutant emissions by 10%–15%.[1] Energy saving and pollution reduction became the strategic theme of the five year plan period.

This redirection of development strategy naturally stirs renewed interests in measuring the quality of economic growth taking account of environmental factors. In the past, people attempted to measure quality of growth in two ways. Firstly, efforts had been made to measure Green GDP, which deducts market values of environmental externalities from normal measure of GDP to obtained a measure of adjusted GDP (e.g., Nordhaus & Tobin, 1972; State Environmental Protection Administration (China), 2006; Boyd, 2007). It is undoubted that Green GDP is a more complete measure of growth quality than the traditional GDP measure for its inclusion of environmental cost to economic growth. However, two drawbacks of Green GDP were identified: 1) measurement issue induced by the fact that damage to environment and natural resources do not occur simultaneously with the due economic growth; 2) difficulty in pricing the damage to environment and natural resources due to lack of delineation of property rights in environment and natural resources (Ma & Hong, 2004). These difficulties gave rise to the interests in the second measurement of growth quality, the Total Factor Productivity (TFP) Indexes (e.g., Hulten, 2001; Zheng & Hu, 2006). By measuring the efficiency with which an economy can produce output from a given set of inputs, TFP indexes reflect the impact of technological progress and efficiency improvement

* Corresponding author.
E-mail addresses: fanx@pku.edu.cn (F. Xia), xujt@nsd.pku.edu.cn (J. Xu).

[1] The 13th Five-Year Plan for Economic and Social Development of the People's Republic of China, available at http://www.gov.cn/

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during the process of economic growth, therefore measures quality of economic growth (Krugman, 1994). To take environmental performances into account, Green TFP (GTFP) indexes can be developed by incorporating environmental variables based on traditional TFP indexes, measuring ability of an economy to produce output from a given set of inputs meanwhile minimizing negative environmental consequences. The two reasons that, 1) TFP has long been used as measurement of development and growth quality; 2) it is easy to incorporate environmental variables in the calculation of TFP, make the measurement of TFP indexes a feasible and low-cost option of gauging the quality of economic growth at the national as well as regional levels.

TFP indexes can be estimated in two ways. One is parametric, Stochastic Frontier Analysis (SFA) method. Another is nonparametric Data Envelopment Analysis (DEA) method based on linear programming. Basically, given data of inputs and outputs, these approaches trace out an efficient production frontier and calculate the distances from observed production to the frontier. Huang, Ji, and Xu (2008) calculated TFP indexes from the estimated stochastic frontier function for provinces in China in 1991–2002, with variables of pollution emissions incorporated. The estimated Green Total Factor Productivity (GTFP) indexes differed significantly from the regular indexes of TFP. The method of stochastic frontier function can only identify one decision making unit (DMU) as most efficient one at the frontier, therefore drew criticism as underestimating the efficiency level of the whole sample. Treating undesirable outputs as inputs in the process of estimation is also counter intuitive for many. On the other hand, the nonparametric DEA method has been widely accepted (Zhou, Ang, & Poh, 2008) for at least three advantages. One is the capacity of the method in directly dealing with multiple outputs and inputs. The second is that this method does not require monetized value for environmental variables. Rather, it can use pollution emissions variables directly. The third is the fact that it is particularly suitable for analyzing data from a small sample. Moreover, a recent work of Zhou, Delmas, & Kohli, (2017) proved mathematically that indexes developed from DEA are cardinally meaningful, allowing comparison over time and space, making it a more convincing approach to evaluate growth quality among different economies.

In this paper, we tried to estimate GTFP indexes using nonparametric method along the line of distance function approach, which possesses the advantages of DEA and on which various ways of defining distance and measuring efficiency has been developed based. The radial technical efficiency measures were first developed by Farrell (1957). Different from static TFP indexes, Caves, Christensen, and Diewert (1982) defined the input-based Malmquist productivity index as the ratio of two input distance functions to measure productivity changes. Färe, Grosskopf, Lindgren, and Roos (1994) extended the Caves et al. approach and developed a Malmquist index of productivity that could be decomposed into indices describing changes in technology and efficiency.

The theoretical underpinning of incorporating environmental factors was developed by Färe, Grosskopf, Lovell, and Pasurka (1989), which modified the standard Farrell efficiency measurement by relaxing the strong disposability of outputs assumption and allowing for the weakly disposability of undesirable outputs. We adopted the methodology of Directional Distance Function (DDF) well developed by Chung, Färe, and Grosskopf (1997) based on previous work, allowing for simultaneously rewarding increase of desirable outputs and decrease of undesirable outputs. They also constructed Malmquist-Luenberger productivity index (ML index) to document dynamic productivity changes when undesirable outputs exist. The ML index is an extension of Malmquist index, which can also be decomposed into efficiency shift and technology shift. DDF models have been widely applied to measure efficiency scores and have been further developed and extended ever since. For examples, the non-radial DDF was proposed to allow non-proportional changes in inputs or outputs (e.g., Fukuyama & Weber, 2009; Zhou, Ang, & Wang, 2012); the concept of meta-frontier was introduced to deal with technology heterogeneity (e.g., Battese, Rao, & O'Donnell, 2004; Wang, Su, Zhou, & Chiu, 2016).

Since the core purpose of this study is to construct indexes to evaluate the growth quality across provinces in China, we follow the classic DDF model which is enough to make comparisons over time and across regions,[2] with modifications to address the inconsistency issue of ML index (Aparicio, Pastor, & Zo_o, J. L., 2013). We also change the direction vectors employed in the DDF to test the sensitivity of results to the model choice.

DDF approach has also been used to estimate GTFP indexes in China in recent years (e.g., Chen & Golley, 2014; Hu, Zheng, Gao, Zhang, & Xu, 2008; Wang, Wu, & Yan, 2010). The study most related to ours is Hu et al. (2008). They also used DDF to evaluate provincial efficiency scores including environmental variables, but they did not calculate the ML indexes which also reflect efficiency changes over time. What's more, one critical drawback of the nonparametric method adopted in previous related studies is that it is deterministic and sensitive to the sampling variations. In this paper, we followed Simar and Wilson (1998), Jeon and Sickles (2004), applying the bootstrap method to obtain the statistical significance of the estimates and ML index. Overall, we chose the most appropriate method and polished up the process of estimating GTFP indexes in a more sound, complete and systematic way, to re-examine the quality of economic growth for provinces in China.

To calculate the green productivity growth for Chinese provinces, we derived the most reliable data that is available from national and provincial statistic year books during 1997 to 2015, treating capital and labor as input, GDP as good output, and various industrial wastes as undesirable output. Here are three highlights of our findings. First, we found that there was little evidence on either TFP growth or GTFP growth for most provinces in most years, despite dramatic and continuous GDP growth. Young (2003) estimated the growth of TFP during the first two decades of reform period (1978–1998) in China to be 1.4% per year, which was moderate compared to the speed of GDP growth (Young, 2003). It is shocking to us that TFP growth rate even became negative afterwards and displayed a declining trend, though GDP kept the rapid growth rate. Negative TFP growth after 1994 was also found by Cao et al. (2009) when studying productivity growth of industries in China. After adjusted by environmental factors, the GTFP growth was also negative in most cases. The great economic growth in China could not be contributed to efficiency improvement in traditional economic input factors and environmental factors. But good news is that after 2007, the overall GTFP growth moved in an opposite direction from the declining TFP growth, which might be evidence of more efforts on reducing pollution put by the government since the eleventh five-year plan (2006–2010).

[2] Though indexes become smaller using non-radial DDF than radial DDF, the cardinal rankings of DMUs remain the same (Zhou et al., 2012).

Second, economic growth measured by GTFP also exhibited divergent spatial distribution among provinces from that produced by GDP growth and the traditional TFP growth. Provinces with highest GDP growth did not necessarily have good performance in terms of TFP growth. Province rankings based on TFP growth also differ from results based on GTFP growth. For example, Inner Mongolia had the highest GDP growth, but ranked the last in terms of TFP growth, and ranked middle after incorporating environmental variables. Therefore, to compare quality of economic growth across provinces highlighting both efficiency and sustainability, an evaluating system based on GTFP rather than GDP or traditional TFP is necessary.

Third, Beijing and Shanghai are the two exceptions that experienced substantial increased GTFP growth. As the two largest megacities located at two major metropolitan areas in China, Beijing and Shanghai rely more on service industry than manufacture sectors, producing much fewer industrial wastes per GDP compared to other provinces. They are also the cities with most stringent environmental regulations. To hold large international events, such as 2008 Olympic Games in Beijing, 2010 World Expo in Shanghai, the local government took many actions to improve air quality and reduce emissions. For Shanghai, TFP growth and GTFP growth shared similar trends, implying TFP increase contributed to GTFP growth, but GTFP growth rates still outperformed TFP growth rates. By contrast, TFP degradation was witnessed in Beijing, thus improvement in GTFP was totally driven by good environmental performance. This might be because that government compulsory regulations, rather than promotion of production and energy efficiency, played a more important role in GTFP growth in Beijing than in Shanghai.

This paper is structured in the following way: the second section is introduction of models of Malmquist-Luenberger indexes and the bootstrapping algorithm; the third section is about the data; the fourth section presents the results of GTFP estimation incorporating environmental variables and analysis of growth quality for 30 provinces in China; Section 5 concludes.

2. The model

Inputs and outputs information of a specific DMU forms one production observation. Given a set of production observations from different DMUs, DEA method can illustrate the efficient productivity frontier. Efficiency scores for each DMU can be estimated then by measuring its distance to the frontier.

To define the green productivity index based on output-oriented distance function, which compares outputs differences among DMUs given exactly same inputs, we set up the model below.

There are K decision making units k = 1, 2, …, K, which are provinces in China in this analysis, using N types of inputs, $x^t \in R_+{}^N$, to produce M types of desirable outputs $y^t \in R_+{}^M$ and L types of undesirable outputs $b^t \in R_+{}^L$ at the same time, where the superscript t denotes time period, $t=1,2,\ldots,\ T$.

Production technology F^t for each time period can be described as:

$$F^t = \{(x^t, y^t, b^t) \mid x^t \ can\ produce\ (y^t, b^t)\} \tag{1}$$

Additionally, different from cases without bad outputs, two assumptions are imposed to address the properties of undesirable outputs. First, weak disposability of outputs highlights that the reduction of bad outputs is costly:

$$(x^t, y^t, b^t) \in F^t and\ 0 \le \theta \le 1\ imply\ (x^t, \theta y^t, \theta b^t) \in F^t \tag{2}$$

Second, good inputs are jointly produced with bad outputs:

$$if\ (x^t, y^t, b^t) \in F^t and\ b^t = 0,\ then\ y^t = 0 \tag{3}$$

2.1. The Malmquist-Luenberger index

2.1.1. The directional distance function

Distance functions measure the distance of observations of production (x^t, y^t, b^t) to the efficiency boundaries at time t. The reciprocal of distance functions is known as Farrell efficiency measure (Farrell, 1957). Chung et al. (1997) introduced the directional output distance function formally defined as:

$$\overrightarrow{D}_o^t (x^t, y^t, b^t; g) = \sup\{\beta \mid (y^t + \beta g_y, b^t + \beta g_b) \in P(x^t)\} \tag{4}$$

Where $P(x^t) = \{(y^t, b^t) \mid (x^t, y^t, b^t) \in F^t\}$; g_y and g_b are subvectors for y^t and b^t of direction vector g.

To credit the increase of desirable outputs and the simultaneous reduction of undesirable outputs, $g = (y, -b)$ is chosen in this paper, which is a popular and reasonable choice in empirical studies of environmental efficiency (e.g., Chen & Golley, 2014; Jeon & Sickles, 2004; Kumar, 2006).

The directional distance function can be computed by solving the following linear programming problems with (y,-b) as the direction vector. As an example, for DMU k:

$$\overrightarrow{D}_o^{t,k} (x^{t,k}, y^{t,k}, b^{t,k}; y^{t,k}, -b^{t,k}) = \max \beta \tag{5}$$

$$s.\ t.\ \sum_{k=1}^{K} z_k y_{k,m}^t \ge (1+\beta) y_{k,m}^t,\ m = 1,\ \ldots, M$$

$$\sum_{k=1}^{K} z_k b_{k,l}^t = (1-\beta) b_{k,l}^t,\ l = 1,\ \ldots, L$$

$$\sum_{k=1}^{K} z_k x_{k,n}^t \le x_{k,n}^t,\ n = 1,\ \ldots, N$$

$$z_k \ge 0,\ k = 1,\ \ldots, K$$

To test the sensitivity of results to the direction vector choice, we also use the Shephard output distance function (Shephard, 1970), which is equivalent to DDF when g = (y, b), requiring proportional expansions in good and bad outputs as much as it is feasible (See Appendix 1 for details).

2.1.2. Productivity measurement

Similar to output-oriented Malmquist productivity defined by Färe et al. (1994) as the geometric mean of two Malmquist productivity indexes based on Shephard's output distance function, the Malmquist-Luenberger (ML) productivity index is defined as:

$$ML_t^{t+1} = \left[\frac{(1+\overrightarrow{D}_o^t(x^t, y^t, b^t; y^t, -b^t))}{(1+\overrightarrow{D}_o^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))} \times \frac{(1+\overrightarrow{D}_o^{t+1}(x^t, y^t, b^t; y^t, -b^t))}{(1+\overrightarrow{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))} \right]^{1/2} \tag{6}$$

The ML index can further be decomposed into product of two components, efficiency change (MLEFFCH) and technology change (MLTECH):

$$MLEFFCH_t^{t+1} = \frac{(1+\overrightarrow{D}_o^t(x^t, y^t, b^t; y^t, -b^t))}{(1+\overrightarrow{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))} \tag{7}$$

$$MLTECH_t^{t+1} = \left[\frac{(1+\overrightarrow{D}_o^{t+1}(x^t, y^t, b^t; y^t, -b^t))}{(1+\overrightarrow{D}_o^t(x^t, y^t, b^t; y^t, -b^t))} \times \frac{(1+\overrightarrow{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))}{(1+\overrightarrow{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))} \right]^{1/2} \tag{8}$$

The $MLEFFCH_t^{t+1}$ measures the change in relative efficiency between t and $t+1$, and the $MLTECH_t^{t+1}$ measures the shift in the frontier with the geometric mean of the technical change between t and $t+1$ using input vectors from the two periods. These indexes indicate productivity improvements if their values are greater than one.

By solving linear programming problems for the four distance functions in formula (6), constructions of the ML indexes can be carried out. However, the usual interpretation of the technical change component can be inconsistent with its numerical value. Therefore, we followed the solution proposed by Aparicio et al. (2013) based on incorporating a new postulate for the technology related to the production of bad outputs to address this inconsistency issue.

2.2. Bootstrapping the Malmquist-Luenberger indexes

The Malmquist-Luenberger index and its two component indexes provide the point estimates of productivity growth rates and respective contributions of efficiency and technology. These estimates are subject to uncertainty due to sampling variation. The bootstrapping method can be applied to DEA estimates (Simar & Wilson, 1998) to provide statistical properties. Simar and Wilson (1999) extended this to estimate the statistical properties of Malmquist index. Simar, Vanhems, & Wilson, (2012) further extended the bootstrap procedure to the context of the DDF, but they imposed a strong disposability assumption on all the inputs and outputs without presence of undesirable variables. Jeon and Sickles (2004), to the best of our knowledge, were the first to apply bootstrap method to ML indexes constructed from directional distances taking account of undesirable outputs. Applications of the bootstrap procedure to the DEA estimators in the energy and environmental field has become more popular in recent years (e.g., Duan, Guo, & Xie, 2016; Zhou, Ang, & Han, 2010).

The basic idea of bootstrap is that by resampling based on simulating data generating process (DGP), the simulated samples will mimic the sampling distribution of original estimators, then estimation bias and confidence intervals can be inferred. The key behind bootstrapping is how to simulate the DGP reasonably. Here we illustrate the smoothed bootstrapping algorithm we used in this article generally in five steps.

First, we compute the estimators of $\widehat{D}_k^t(x_k^t, y_k^t, b_k^t)$, $\widehat{ML}_k(t, t+1)$ from the original sample $X = \{(x_k{}^t, y_k{}^t, b_k{}^t) | k = 1, 2, \ldots, K; t = 1, 2, \ldots, T\}$.

Second, using smooth bootstrap, we generate a random sample of simulated distance function values Γ^* to form pseudo-samples X^*. Since the possibility of temporal correlation in the panel data, the bivariate kernel estimator of the joint density of the original distance function estimates $\{\widehat{D}_k^t(x_k^t, y_k^t, b_k^t), \widehat{D}_k^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})\}_{k=1}^K$ is needed. We follow the algorithm developed by Jeon and Sickles (2004),[3] which involves using kernel methods to estimate the density of the original observations and their reflections about the boundaries in two-dimensional space, to obtain the joint density estimates and then generate Γ^*.

Third, we calculate four distance functions using the pseudo-sample X^*, $\widehat{D}_k^{*t}(x_k^t, y_k^t, b_k^t)$, $\widehat{D}_k^{*t+1}(x_k^t, y_k^t, b_k^t)$, $\widehat{D}_k^{*t}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})$,

[3] See Appendix B in Jeon and Sickles (2004) for full detailed algorithm.

$\widehat{D}_k^{*t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})$ which are needed to construct the indexes $\widehat{ML}_k^*(t, t+1)$, $\widehat{MLEFFCH}_k^*(t, t+1)$, and $\widehat{MLTECH}_k^*(t, t+1)$.

Fourth, we repeat the second and third steps for B = 1000 times to get a set of bootstrap estimates for each DMU. Then the known distribution of bootstrap estimates will mimic the unknown distribution of original estimators, for example, $(\widehat{ML}_k^* - \widehat{ML}_k) \sim (\widehat{ML}_k - ML_k)$ (time indicators of the indexes are omitted for simplicity).

Fifth, we correct the estimation bias of original estimators, e.g. $bias_k = \mathrm{E}(\widehat{ML}_k) - ML_k$ can be estimated as

$$\widehat{bias}_k = \frac{1}{B}\sum_{b=1}^{B}\widehat{ML}_{kb}^* - \widehat{ML}_k = \overline{\widehat{ML}}_k^* - \widehat{ML}_k \tag{9}$$

Then the bias-corrected ML index will be

$$\widetilde{ML}_k = \widehat{ML}_k - \widehat{bias}_k \tag{10}$$

Confidence intervals can also be obtained with the set of bootstrap estimates.

3. Data of provincial inputs and outputs

To compare growth quality among provinces in China, we chose labor and capital stock as the inputs, GDP as the desirable output, and quantity of industrial waste gas emission, industrial waste water emission, industrial waste solid generation as measures of undesirable outputs.[4]

We obtained yearly data of 30 provinces[5] from 1997 to 2015 from national and provincial statistical yearbooks and environmental yearbooks.

3.1. Inputs

Standard labor time spent on production is the better measurement of labor inputs. In practice, we used number of yearly laborers from provincial Statistical Yearbooks as measure of labor inputs, since this is the best data available.

Capital stock is estimated through the widely used "Perpetual Inventory Method" introduced by Goldsmith in 1951 (Goldsmith, 1951) expressed as:

$$K_k^t = K_k^{t-1} + I_k^t - D_k^t \tag{11}$$

where t stands for time; k stands for province; K stands for capital stock; and I stands for investment; D stands for capital depreciation.

Data for four variables are critical to estimate capital stock. They are yearly investment, investment price index, capital stock for the base year and depreciation. Based on estimation of China's provincial capital stock from 1952 to 2000 by Zhang, Wu, and Zhang (2004), we directly used their estimation in 2000 as the base year capital stock. Following their suggestion, Gross Fixed Capital Formation[6] from China Statistical Yearbook (National Bureau of Statistics of China) is used as the measure of investment. Fixed Capital Price Index series and Fixed Capital Depreciation can also be obtained from China Statistical Yearbook.

3.2. Outputs

GDP data is collected from China Statistical Yearbook and measured at 1978 price.

Undesirable outputs include levels of total volume of industrial waste gas emission, total volume of industrial waste water discharged, and total industrial solid wastes generation from China Statistical Yearbook on Environment (Ministry of Environmental Protection). We choose the indicators of three industrial wastes for the following two reasons.

First, the three industrial wastes emission are the most comprehensive measures of pollution production. As the economy grow to different stages and as our understandings toward pollution develop, the major pollutants to focus on might evolve, e.g., from SO_2 to NOx in terms of gaseous pollutants, therefore the statistics worked and published evolve correspondingly. Indicators of specific pollutants might not reflect the pollution severity, e.g., we might misinterpret the decrease in SO_2 emission as signals of better environment when neglecting increases in NOx. Despite the actual environmental damages also depend on pollutant concentrations, the amount of wastes could at least reflect a comprehensive level of burden for the environment. What's more, as the emission standards tighten over time, we have a good reason to believe the pollutant concentrations would not increase in the waste gas or waste water, thus decreases in amount of wastes discharged do signal better environment performances.

Second, the three industrial wastes emission are the most consistent measures all the time. As they are the very first measures and focuses of environmental damages due to economic activities in China since 1970s, they are also the most consistent indicators

[4] Estimation of ML indexes with distance function method does not require value information for all variables.

[5] Tibet is excluded from our analysis due to missing data.

[6] According to the definition by National Bureau of Statistics, the total fixed capital formation includes the values of residential buildings, other buildings and structures, machineries and equipment, cultivated biological resources, intellectual property products (R&D expenditures, mineral exploration, computer software) minus those are disposed. It has been widely accepted as the reasonable indicator of yearly new investment in studies about China, while the accounting method of deducting certain assets from total investment has been controversial (Shan, 2008; Zhang et al., 2004).

available across the years. While, e.g., NOx in waste gas has not been monitored and reported nationally until 2004.

SO_2 emission and Chemical Oxygen Demand (COD) are also often chosen as undesirable outputs (Tu, 2008; Wang et al., 2010; Watanabe & Tanaka, 2007), because they are the major monitored pollutants, and the central government set respective reduction goals for them during every five-year plan period. However, as we mentioned above, indicators of specific pollutants might be misleading when major pollutants change as the economy develops. Besides, the data quality of SO_2 and COD emission has been questioned (Wang & Huang, 2015). It is highly possible the data was modified to reach the goals. Therefore, we prefer the industrial wastes as measures of undesirable outputs in the main analysis to evaluate pollution across provinces comprehensively.

For industrial wastes, there are also many indicators in statistical books, and we choose indicators 1) consistently reported as many years as possible, 2) measure environmental burdens in a stricter way. Intuitively, net emission, such as total wastes discharged deducting the volume meeting emission standards, could better represent the environmental performances, but such data for industrial waste water and gas is not available after 2010. For the solid wastes, it is hard to define and infer the net emission because they could be stocked and treated years after.[7] Nevertheless, we argue that the total volume of wastes discharged is also a good measure, because even wastes up to the discharge standards still contain pollutants and could harm the environment, and the tightening standards and increasing treatment capacity actually make the total emission a stricter indicator to evaluate environmental burdens.

The emissions of industrial wastes on statistic year books are originally provided by Ministry of Environmental Protection (currently Ministry of Ecology and Environment), collected from polluting sources by local administrations of environmental protection. According to the technical guidelines for environmental statistics - pollution sources statistics (HJ 772-2015), the generation and emission data sources of waste gas, waste water and solid waste for pollution sources, are from their production reports and operation reports of pollution control facilities. The accounting methods, which could infer emission from 1) monitored pollutant concentration data, 2) the balance of mass during production, or 3) inputs/outputs weighted by emission coefficients, depend on data availability according to pollutants, industries, production processes, etc. The environmental statistics reported by the government is the most systematic and consistent data source with easy access and low cost.

It is possible that local governments have incentives to under report pollution emissions, but relative to the accuracy of exact numbers, the consistency is more important to make comparisons among provinces and across time for the purpose of this study. We admit that discrepancies in the data generation processes among local administrations could result in biases of our GTFP estimations. If provinces with higher levels of economic growth, capable of devoting more on the data collection systems, can provide more accurate data, while the other provinces might understate, rankings of GTFP for the more developed regions could be underestimated.

Finally, to include broader environmental damages and take account of energy efficiency, as well as test the sensitivity of the results to the choice of environmental variables, we also add CO_2 emission as the undesirable output (Appendix 1). That is to say, given the same labor and capital input, the economy generating more GDP meanwhile less wastes and less CO_2, is considered to be more efficient. We choose to do so rather than treating energy use as a separate input mainly because 1) CO_2 emission is calculated from energy use and can reflect impacts of both energy consumption and energy structure; 2) all the indexes constructed in this study are out-oriented, i.e., comparing outputs given the same inputs, thus we try to keep the consistency of input variables in order to compare with results from most related previous studies.

Provincial CO_2 emission data comes from results published by China Emission Accounts and Datasets (CEADs) inferred from latest energy data revision (2015) by Chinese Statistics Bureau.[8]

3.3. Summary statistics

Table 1 summarizes the average levels of all inputs and outputs from 1997 to 2015 for 30 provinces in China. Jiangsu province had the largest GDP volume over the 19 years. The second largest economy in terms of GDP was Guangdong. Shandong province ranked first in labor input and capital input. Hebei province was a large polluter producing the most industrial waste gas and solid wastes as well as over 1.1 billion tons of waste water, which was more than 1.5 times that of average emission level. For Jiangsu, the 808.8 billion Yuan GDP per year on average was based on 2.4 billion tons of industrial waste water discharge, even twice as much as Hebei, and considerable amount of the other types of industrial wastes.

The average growth rates of all inputs and outputs are presented in Table 2. The average national GDP growth rate over 1997–2015 was 10.5%, with GDP of all provinces increasing at average rates above 9%. The mean level of labor inputs growth rates was 1.5% nationwide. Beijing, Tianjin, and Fujian enjoyed the most labor inflows with yearly growth rates above 3%, while Chongqing and Gansu experienced no increment in labor supply on average. Capital stocks in all provinces also rose at an amazing speed. The nationwide average growth rate was 16.1% every year. Nationally, the industrial waste water discharge was best treated among three types of industrial wastes, increasing 0.5% per year averagely. However, industrial waste gas and solids had been rising at rates of 13.6% and 10.8% respectively. Beijing outperformed all the other provinces in controlling industrial wastes emissions, with only slight augment in waste gas and reductions in waste water and solids.

[7] The solid wastes discharged is another indicator provided in the statistical year books, referring to the amount of solid waste emitted outside the solid waste treatment facilities and sites. It is used as the alternative measure for industrial solid wastes as a robustness check in Appendix 1.

[8] CO_2 emission data available at http://www.ceads.net.

Table 1
Average levels of inputs and outputs over 1997–2015, by province.

Province	Labor (10^4)	Capital (10^8 CNY)	GDP (10^8 CNY)	Industrial waste gas emission (10^8 m^3)	Industrial waste water discharged (10^4 tons)	Industrial solid wastes produced (10^4 tons)
Beijing	884	19,475	1927	3735	15,240	1155
Tianjin	631	15,988	1752	5270	20,442	1139
Hebei	3683	31,884	3531	38,532	110,112	21,297
Shanxi	1583	13,160	1330	20,851	40,149	15,523
Inner Mongolia	1154	18,803	1545	17,553	28,760	11,011
Liaoning	2179	27,653	3358	21,522	94,512	15,487
Jilin	1253	16,264	1408	6083	38,725	3134
Heilongjiang	1792	15,882	1828	7179	47,303	4398
Shanghai	993	24,864	4471	9399	57,603	1886
Jiangsu	4507	51,842	8088	26,827	243,371	6695
Zhejiang	3248	37,102	4401	15,223	165,349	2995
Anhui	3795	16,462	2227	13,809	67,665	6674
Fujian	2043	22,139	2363	8548	103,152	4411
Jiangxi	2323	11,855	1510	7370	59,216	7610
Shandong	5962	52,171	6236	29,032	151,019	11,703
Henan	5777	36,951	3596	19,908	122,094	8514
Hubei	3536	19,812	3030	11,832	97,429	4792
Hunan	3817	20,057	2180	8936	107,285	4546
Guangdong	5030	44,280	7545	17,374	169,466	3696
Guangxi	2702	16,202	1232	12,058	115,414	4600
Hainan	408	3282	371	1257	6954	206
Chongqing	1587	12,954	1291	5808	67,514	2108
Sichuan	4727	22,352	3097	12,390	100,532	8220
Guizhou	1918	7863	710	8770	20,362	5271
Yunnan	2559	13,933	1081	8134	37,458	7797
Shaanxi	1957	16,366	1488	8213	37,768	5032
Gansu	1487	5526	894	6453	20,933	3324
Qinghai	296	3047	175	2684	6408	3994
Ningxia	307	3620	207	4992	15,176	1483
Xinjiang	845	11,217	717	7634	22,370	3190
Total mean	2433	20,434	2453	12,226	72,993	6063

Notes: Raw data of capital, GDP and Industrial wastes for provinces comes from National Statistical Year Books. GDP is calculated at 1978 price. Mean values over 1997–2015 are reported for each province.

4. Results of provincial Green Total Factor Productivity indexes

4.1. Results of Malmquist-Luenberger indexes

After calculating the GTFP growth measured by Malmquist-Luenberger productivity change index and its components indicating efficiency change and technological change, bootstrap method described in Section 2.2 was implemented, and original estimates were corrected for bias and statistical significance of the estimates were tested.[9]

Table 3 lists the results of the ML indexes.[10] Values larger than one indicating productivity efficiency improvement relative to last year, while values less than one indicating relative declines in productivity. Stars suggest whether values are significantly different from unity at the 95 percent level. Distribution of ML indexes and their decomposition indexes for 30 provinces over 1998–2015 are graphed in Fig. 1 (right panel). For most provinces over these 18 years, the ML index ranged around 0.8–1.2, corresponding to 20% decrease to 20% increase of GTFP. The largest statistically significant number went to Tianjin and Chongqing in 2011 which suggests a 30% and 29% growth of GTFP.

According to Table 3, Beijing showed continuous improvement in GTFP except 2010, though not significant after 2003. As another city in Jing-Jin-Ji region, Tianjin also went through generally enhanced green productivity, which became even greater and more significant after 2010. To the very contrast, GTFP of Hebei kept falling until 2011. This might reveal the fact that development of Beijing in the past years relied most on service industry, meanwhile most polluting industries were moved outside to Hebei.

Provinces in northeast, Liaoning, Jilin and Heilongjiang, displayed similar change patterns, where ML indexes were over one in the late 1990s – early 2000s, and fell below one afterwards.

In the eastern coastal region, green productivity was steadily improved only in Shanghai, although not significantly. Other provinces like Jiangsu, Zhejiang didn't experience significant changes in green productivity efficiency.

However, ML indexes below 0.9 and statistically significant can be frequently found in western provinces, Gansu, Qinghai, Ningxia and Xinjiang.

[9] We solved the programming problems and implemented bootstrapping using Matlab with Data Envelopment Analysis Toolbox developed by Álvarez, Barbero, and Zofío (2016) as the basis for modification.

[10] See Appendix 3 for figures of time trends of ML indexes measuring GTFP growth for each province.

Table 2
Average growth rates of inputs and outputs over 1997–2015, by province.

Province	Growth rates (%)					
	Labor	Capital	GDP	Industrial waste gas emission	Industrial waste water discharged	Industrial solid wastes produced
Beijing	3.5	13.4	10.0	1.4	−7.0	−1.9
Tianjin	3.2	18.1	12.8	11.5	0.6	7.5
Hebei	1.3	15.9	9.7	14.8	1.9	12.8
Shanxi	1.5	17.5	9.9	11.9	1.0	13.0
Inner Mongolia	1.9	22.1	13.2	14.1	2.4	15.2
Liaoning	1.2	15.2	10.3	9.9	−1.6	9.9
Jilin	1.2	18.0	10.6	7.1	0.0	7.3
Heilongjiang	1.2	13.6	9.3	5.9	−2.8	5.0
Shanghai	1.5	12.0	9.8	6.0	−3.8	2.3
Jiangsu	1.0	15.1	11.3	12.6	0.1	8.1
Zhejiang	2.0	15.6	10.4	11.9	4.0	8.8
Anhui	1.5	14.5	10.4	13.9	0.0	9.2
Fujian	3.1	16.6	11.0	14.6	4.7	18.0
Jiangxi	1.2	15.5	10.5	14.2	2.2	6.4
Shandong	1.3	15.3	11.1	10.8	2.3	8.3
Henan	1.8	17.9	10.3	11.2	2.1	9.9
Hubei	0.6	17.5	10.7	11.1	−1.9	8.3
Hunan	0.6	15.7	10.6	9.0	−3.4	10.3
Guangdong	2.9	13.7	10.7	9.9	2.2	8.7
Guangxi	0.8	19.2	10.5	11.8	0.6	9.1
Hainan	2.7	13.5	10.0	16.2	0.2	12.9
Chongqing	0.0	16.6	11.5	12.3	−5.0	5.0
Sichuan	0.2	14.6	10.7	11.1	−1.9	8.5
Guizhou	0.5	16.4	10.8	16.6	1.4	13.8
Yunnan	1.6	16.6	9.5	13.4	1.7	12.8
Shaanxi	0.8	16.5	11.2	11.9	2.2	9.0
Gansu	0.0	15.4	9.6	11.3	−3.0	9.0
Qinghai	1.0	18.4	10.8	15.1	6.0	46.2
Ningxia	2.0	18.2	10.3	20.2	6.8	13.9
Xinjiang	2.9	15.0	9.1	15.3	3.2	15.9
Total mean	1.5	16.1	10.5	13.6	0.5	10.8

Decomposition results of ML indexes into efficiency change (MLEFFCH) and technological change (MLTECH) are presented in Tables 4 and 5. Technological changes were in general positive but insignificant. Significant MLEFFCH indexes below one appeared more frequently than those over one. The distribution of these indexes can be more clearly seen in Fig. 1. MLTECH indexes measuring technology shift centered around 1, indicating no significant degradation nor advancement in technology. While MLEFFCH indexes for efficiency were more distributed on the side of less than 1, indicating degeneration in efficiency. That is to say, it is efficiency degeneration that contributed most to the GTFP declines. For example, before 2011, MLEFFCH indexes of Hebei almost kept significantly below one, while MLTECH indexes kept around one. Thus, it was the relative efficiency backsliding that led to negative GTFP growth of Hebei before 2011. For Beijing and Shanghai, the only two cities enjoyed continuous fast GTFP growth, efficiency changes were mostly positive but small in magnitude and insignificant. Instead, technology improvements were much larger in magnitude and more significant. That means GTFP growth of Beijing and Shanghai resulted most from remarkable technological progress.

To investigate how sensitive the results of GTFP are if choosing different models or environmental outcomes, we conduct several robustness checks. First, we use the Shephard distance function. Second, we replace the indicator of industrial solid wastes produced with the industrial solid wastes discharged. We also remove the solid wastes and only include industrial waste gas and water. Third, we add CO_2 emission as the fourth undesirable output to incorporate energy factor. Details and results are presented in Appendix. In general, the results are robust to our baseline model, therefore we still focus on the results with industrial wastes emission in the following analysis.

4.2. Comparison of GDP growth, TFP growth and GTFP growth

To compare results of GTFP growth with GDP growth, the most widely recognized indicator of economic growth, and with the traditional TFP, measure of productivity efficiency considering inputs and only good outputs, we defined and calculated another two variables, GDPr and Mb. GDPr is the ratio of current period GDP to previous period GDP. Thus, a GDPr greater than one reflects GDP growth. Mb is the bias-corrected Malmquist index after bootstrapping, which completely ignores undesirable outputs that are harmful to the environment. Mb was obtained based on Shephard output distance function, documenting the traditional productivity changes in the ability to produce more GDP given the same labor and capital inputs. Similarly, values of Mb greater than one represent productivity growth. As described in Section 2.1.1, Shephard output distance function is a special case of DDF, thus the results of ML and Mb are derived from same methodology and are comparable.

Table 3
Green total factor productivity change index for provinces, 1998–2015.

Province	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Beijing	1.08	1.19*	1.24*	1.12	1.14*	1.23*	1.11	1.09	1.15	1.16	1.12	0.99	0.92	1.08	1.23	1.02	1.06	1.14
Tianjin	1.05	1.23*	0.90	0.81*	0.95	1.10	1.11	0.51*	1.22*	1.13*	1.08	1.11	0.90	1.30*	1.25*	1.16*	1.08	0.99
Hebei	0.72*	0.97	0.97	0.83*	0.98	0.99	0.89*	0.97	0.94	0.90	0.80*	0.90	0.93	1.07	1.01	1.07	0.98	1.03
Shanxi	0.94	0.91*	1.02	0.97	1.03	1.02	0.97	0.94	0.75*	0.92	0.78*	0.86*	0.81*	1.23*	0.90	0.99	0.93	1.06
Inner Mongolia	1.06	1.02	1.04	1.03	0.93	0.90*	0.93	0.93	0.88*	1.11	0.82*	0.98	0.61*	1.10	1.13	0.91	0.95	1.01
Liaoning	1.09	1.11	1.14*	1.10*	1.08*	1.08*	0.85*	0.88	0.87*	0.82*	0.65*	0.97	0.96	0.96	1.07	1.08	0.84*	1.08
Jilin	1.12*	1.06	1.04	1.02	1.00	1.00	0.95	0.84*	0.85*	1.02	1.05	0.83*	1.03	0.87	0.97	1.03	0.99	0.81*
Heilongjiang	1.11*	1.08*	1.03	1.09	1.13*	1.02	1.12*	1.00	0.98	0.88	0.98	0.89	1.04	1.09	0.97	0.98	0.85*	1.00
Shanghai	1.21*	1.07	1.04	1.07	1.05	1.10	1.11	1.09	1.22*	1.18	0.98	1.06	0.95	1.05	1.09	1.05	1.08	0.90
Jiangsu	1.13*			0.98			0.94	0.93	0.97	0.96	1.00	0.98	0.96	0.85	0.90	0.91	0.96	0.87*
Zhejiang	0.75*	0.93	0.92	0.93	1.02	0.94	1.02	1.06	0.89	0.97	1.08	0.96	1.06	0.94	1.00	1.04	0.91	0.98
Anhui	1.10*	0.99	1.01	0.96	1.03	0.98	0.96	0.94	0.90	0.92	0.96	0.99	0.95	0.93	0.90	0.88	0.93	0.94
Fujian	0.91	0.91	0.88*	0.94	1.00	0.84*	0.89*	0.78*	1.00	0.74*	1.21*	0.72*	1.05	1.03	0.98	0.96	0.92	1.00
Jiangxi	1.06	1.01	0.98	1.12*	0.94	0.85*	0.83*	0.84*	0.82*	0.90	0.94	0.98	1.00	0.79*	0.99	0.99	1.06	0.91
Shandong	1.16*	1.11*	1.02	0.97	1.11*	0.97	0.84*	0.90	0.92	0.87	0.89	0.94	0.94	0.98	1.10	1.00	0.94	0.94
Henan	1.00	0.93*	0.91*	0.94	0.97	0.99	0.94	0.95	0.86*	0.78*	1.00	0.84*	1.17*	0.60*	1.06	0.97	0.95	0.99
Hubei	0.96	0.97	0.98	0.95	0.95	0.99	0.86*	0.95	0.90	0.94	0.93			0.86	0.82*	0.85*	0.93	0.90*
Hunan	1.14*	1.02	1.14*	1.03	1.03	0.93	0.91	0.99	1.11*	0.71*	1.09	0.76*	1.02	0.98	1.03	0.97	1.07	0.99
Guangdong	0.99	0.99	1.04	1.02	1.02	1.06	1.05	1.04	1.14	0.99	0.97	0.94	0.95	0.88	0.90	0.96	0.97	0.93
Guangxi	0.98	0.97	0.94	0.91*	1.02	0.93*	0.85*	0.96	0.98	0.85*	1.13*	0.87*	1.12	0.68*	0.95	1.12*	1.04	1.01
Hainan	1.11	1.06	0.80	1.17	0.92	1.12	0.99	0.98	1.01	1.10	0.62*	1.18	1.16	0.43*	0.80*	0.98	0.77*	1.07
Chongqing	1.04	0.98	1.07*	1.22*	1.02	0.86*	0.56*	1.05	0.71*	0.77*	1.14*	0.71*	1.20*	1.29*	1.12	0.97	1.06	0.92
Sichuan	1.11*	0.99	1.01	0.99	0.86*	1.06	0.95	0.97	0.96	0.92	0.93	1.04	0.95	0.99	0.97	1.07	0.98	1.14*
Guizhou	0.91*	1.03	1.14*	0.92*	1.11*	0.92*	0.99	1.09	1.03	1.12*	0.99	0.85*	0.92	0.89	0.97	1.02	0.78*	1.06
Yunnan	1.04	0.89*	0.93*	0.95	0.97	0.89*	0.93	0.94	0.92	0.88*	1.02	0.91	0.99	0.77*	1.07	1.00	0.95	0.88*
Shaanxi	0.75*	1.05	1.10*	0.98	0.91*	0.91*	0.97	0.95	1.01	0.91	0.74*	0.91	1.01	1.03	1.09	1.08	0.97	0.85*
Gansu	1.16*	1.12*	1.07	1.07	1.00	1.01	1.12	0.98	0.94	0.94	0.75*	0.92	0.86	0.88	0.90	0.84*	0.85*	0.84*
Qinghai	1.13*	0.71*	0.98	1.01	1.07	0.86*	0.93	0.66*	0.89*	0.93	0.97	0.85*	0.92	1.01	0.97	1.00	1.01	0.96
Ningxia	0.84*	0.98	0.88*	1.00	0.89*	0.99	1.00	0.76*	1.03	0.90*	0.99	0.94	0.80*	1.02	1.04	1.00	1.00	0.95
Xinjiang	0.78*	0.87	1.22*	0.81*	0.86*	0.89*	0.94	0.90	0.98	0.92	0.95	0.85*	0.87	0.92	0.97	0.92	0.99	0.96

Note: *Significant from unity at 95% confident level.

Distribution of Malmquist index measuring traditional TFP growth mostly ranged from 0.8 to 1.1, i.e., 20% decrease to 10% increase (Fig. 1, left panel). Different from distribution of ML index and its decompositions, distributions of Mb and corresponding decompositions of MEFFCH and MTECH concentrated at less wide ranges when not considering undesirable environmental damages, and both efficiency decrease and technological degeneration contributed to negative TFP growth.

More careful comparisons of GDP growth, TFP growth and GTFP growth were conducted in two dimensions to find out what different stories that GTFP indexes tell us from traditional measures of economic growth. First, we took means of indexes of 30 provinces and obtained the national average growth rates every year to explore whether these three methods of measuring growth exhibit same time trends. Second, average values of indexes through the studied period of every province enable us to easily compare performances across provinces in the context of respective type of growth index.

We also restrict analysis to the secondary industry (largely manufacturing sector) in Appendix 2, computing GDPr, Mb, MLb based on corresponding data in the secondary industry following same procedures, and further making comparisons over time and across regions.

4.2.1. Comparison by time trend

It would be interesting to look at the trends of the three indexes aggregated at the national level over the studied period (Fig. 2). The three indexes behave quite differently.

In terms of absolute values, GDP ratios were always far beyond one until 2015, while TFP growth and GTFP growth ranged from 0.9 to slightly above 1, i.e., TFP and GTFP decreased or stayed constant. The remarkable economic growth was not the fruit of productivity efficiency improvement, and it was accompanied by generally decreasing green efficiency. Evidence of negative TFP growth after 1994 was also provided by Cao et al. (2009) when studying productivity growth of industries in China. Cheng and Li (2009), which studied the national average efficiency scores during 1993–2006, also documented the declining trends of TFP and GTFP. Our results derived at province level and up to date suggest no reverse of the finding that productivity in China is decreasing no matter whether environmental performance is taken into account, in spite of rapidly growing GDP.

Furthermore, patterns of the three growth trends diversified as well. GDP growth rate raised before 2004, then kept around 13%, and gradually slowed down since 2010, and dropped to negative in 2015. TFP growth rate showed an all the way declining trend, especially during 2003–2008 when GDP was rapidly growing, and there was also a sharp drop in 2015 together with GDP growth rate. GTFP growth had similar trend with TFP at the beginning, then exceeded TFP since 2008, and rebounded to one in 2012. Noticeably, GTFP growth exhibited no steep decline in 2015. Along with accelerated GDP growth was the lower and lower efficiency score from late-1990s to mid-2000s. After 2010, the GDP growth slowed down, and TFP growth was still at a low level. But if

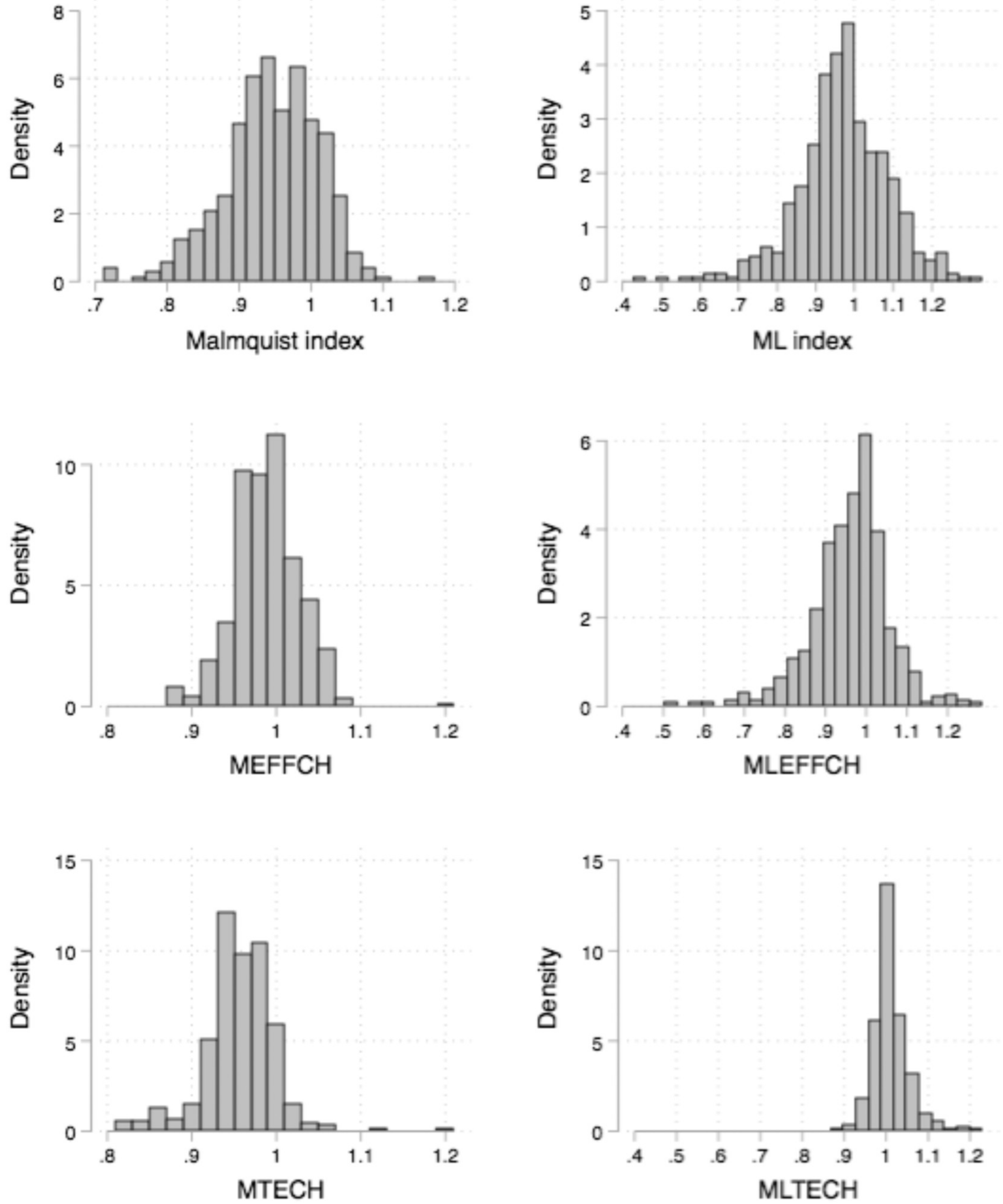

Fig. 1. Distribution of estimated Malmquist and Malmquist-Luenburger indexes.

incorporating environmental factors, the productivity score of GTFP actually performed better than TFP, meaning production was moving towards less pollution given same amount of inputs of labor and capital. The rebound in GTFP growth and trend separation from TFP growth after 2007 make sense, because the government promoted vigorously energy saving and emission reduction programs since the eleventh five-year plan for national economic and social development (2006–2010), which targeted 10% reduction of criteria pollutants emission and 20% reduction of energy consumption per GDP.[11]

4.2.2. Comparison by province

Table 6 gives mean levels of these three indexes over the studied period by province. For all provinces, the average annual GDP growth rate was at least 10%. Except Shanghai, the other 29 provinces or cities experienced average Mb indexes less than one,

[11] When looking into each province separately, the trends of these three indicators were also true for most provinces (Appendix 3 Figs. S5–S7).

Table 4
Efficiency change component index (MLEFFCH) for provinces, 1998–2015.

Province	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Beijing	0.98	1.01	1.12*	1.02	1.02	1.04	1.02	1.02	1.05	1.04	1.01	0.97	0.96	1.02	1.02	1.01	1.02	1.04
Tianjin	1.00	1.03	0.96	0.84*	0.89*	1.01	1.05	0.58*	1.12*	1.04	1.01	1.04	0.92	1.27*	1.17*	1.09*	0.99	1.03
Hebei	0.75*	0.96*	0.95*	0.83*	0.97*	0.97	0.86*	0.97	0.94*	0.91*	0.84*	0.92*	0.92*	1.07	0.99	1.03	0.96	1.03
Shanxi	0.95*	0.89*	0.99	0.94*	0.99	0.99	0.91*	0.91*	0.77*	0.92*	0.82*	0.89*	0.83*	1.21*	0.91*	0.98	0.93*	1.06*
Inner Mongolia	1.03*	1.01	1.01	0.99	0.91*	0.88*	0.87*	0.90*	0.85*	1.05	0.84*	0.97	0.71*	1.10	1.10*	0.93*	0.93*	1.01
Liaoning	1.08*	1.10*	1.12*	1.12*	1.07*	1.07*	0.85*	0.89*	0.86*	0.84*	0.71*	0.98	0.95	0.98	1.04	1.05*	0.85*	1.09*
Jilin	1.08*	1.04*	1.02	1.01	1.00	0.98	0.92*	0.87*	0.85*	0.98	1.04	0.79*	1.11	0.88*	0.92*	1.05*	0.98	0.87*
Heilongjiang	1.06*	1.04*	1.01	1.04*	1.09*	0.98	1.08*	0.96	0.95	0.87*	0.99	0.89*	1.07	1.05	0.92*	0.98	0.86*	1.00
Shanghai	1.01	1.01	0.99	1.01	1.01	1.03	1.02	1.01	1.05	1.04	0.99	1.03	0.98	1.03	1.03	1.01	1.03	0.97
Jiangsu	1.10*	.	.	1.00	.	.	0.91*	0.93*	0.93*	0.94*	1.01	1.00	1.00	0.88*	0.94*	0.95*	0.98	0.96
Zhejiang	0.80*	0.94*	0.92*	0.94*	1.00	0.91*	1.00	1.02	0.86*	0.96	1.06	0.92	1.07	0.93	0.94	1.00	0.90*	0.97
Anhui	1.07*	0.98	1.01	0.96*	1.03*	0.97*	0.94*	0.95*	0.89*	0.91*	0.97	1.01	0.98	0.95	0.93*	0.91*	0.93*	0.97
Fujian	0.97	0.94*	0.95*	0.96	1.00	0.82*	0.89*	0.80*	0.93	0.79*	1.17*	0.66*	1.21*	1.00	0.93*	0.97	0.92	1.01
Jiangxi	1.02	1.02	0.98	1.12*	0.95*	0.86*	0.83*	0.86*	0.81*	0.89*	0.94	0.97	1.03	0.81*	0.98	0.97	1.01	0.91*
Shandong	1.09*	1.05*	1.00	0.94*	1.05*	0.95*	0.82*	0.91*	0.92*	0.87*	0.92*	0.94	1.01	0.96	1.03	0.99	0.93*	0.95*
Henan	0.98	0.92*	0.92*	0.94*	0.97	0.97	0.91*	0.95*	0.86*	0.80*	1.00	0.82*	1.24*	0.67*	1.01	0.97	0.96*	1.00
Hubei	1.00	0.99	0.99	0.98	0.99	1.00	0.87*	0.95	0.90*	0.94*	0.94	.	.	0.89*	0.87*	0.86*	0.92*	0.93*
Hunan	1.09*	1.03*	1.14*	1.03	1.02	0.89*	0.91*	0.96	1.02	0.75*	1.06*	0.73*	1.11*	0.96	0.98	0.96	1.04	1.00
Guangdong	0.99	0.99	1.02	1.00	1.00	1.01	1.02	1.01	1.04	0.99	0.99	0.99	1.00	0.92	0.90*	0.94	0.92*	0.94*
Guangxi	0.97	0.96*	0.94*	0.93*	1.02	0.92*	0.86*	0.96	0.95*	0.87*	1.09*	0.86*	1.13	0.75*	0.96*	1.10*	1.04*	1.02
Hainan	1.04	1.01	0.92	1.07	0.97	1.02	1.00	1.00	0.99	1.03	0.70*	1.09	1.13	0.51*	0.79*	0.95	0.81*	1.08*
Chongqing	1.02	1.00	1.08*	1.20*	1.01	0.84*	0.62*	1.02	0.72*	0.81*	1.11*	0.76*	1.19*	1.23*	1.03	0.98	1.03	0.94*
Sichuan	1.09*	1.00	1.01	1.01	0.88*	1.04	0.94*	0.97	0.93*	0.92*	0.94	1.04	0.97	1.01	0.98	1.04	0.94*	1.10*
Guizhou	0.91*	1.01	1.12*	0.91*	1.06*	0.89*	0.94*	1.03	0.98	1.07*	0.97	0.87*	0.91*	0.92	0.97	1.01	0.81*	1.06*
Yunnan	1.02	0.91*	0.96*	0.95*	0.97*	0.89*	0.93*	0.93*	0.93*	0.89*	1.01	0.92*	1.01	0.81*	1.05*	1.01	0.97*	0.92*
Shaanxi	0.77*	1.00	1.10*	0.98	0.90*	0.89*	0.95*	0.93*	0.99	0.90*	0.79*	0.89*	1.05	1.02	1.08*	1.06*	0.96	0.90*
Gansu	1.14*	1.05*	1.01	1.01	1.00	1.01	1.02	0.99	0.97	0.97	0.80*	0.95	0.90*	0.91	0.93*	0.88*	0.86*	0.89*
Qinghai	1.06*	0.69*	1.00	0.99	1.03*	0.86*	0.92*	0.70*	0.92*	0.96*	0.98	0.91*	0.97	1.01	0.99	1.01	1.00	0.97*
Ningxia	0.87*	0.97*	0.91*	0.99	0.90*	0.97*	0.98	0.79*	1.01	0.92*	1.00	0.96*	0.89*	1.01	1.04*	1.01	1.00	0.97*
Xinjiang	0.79*	0.82*	1.22*	0.82*	0.86*	0.89*	0.92*	0.89*	0.99	0.93*	0.95*	0.88*	0.93*	0.94	0.98	0.94*	1.00	0.97

Note: *Significant from unity at 95% confident level.

representing negative TFP growth. The average TFP growth rates were estimated to be 2% for Shanghai, and −9% to −2% for the other provinces and cities over 1998–2015. Again, based on our estimation, the TFP was not growing at all from 1998 to 2015 for most provinces on average. When including the undesirable outputs, we found the arithmetic mean of ML indexes of the 30 provinces was 0.97, lower than the average ML index for China calculated by Jeon and Sickles (2004), which was 1.015 for 1989–1995, prior to our studied period. Wang et al. (2010) estimated the GTFP growth rate over 1998–2007 to be 1.8% respectively. But they did not apply bootstrap to account for sampling error, and they used data of COD and SO_2 emission, two main indicators that strict goals are set by central government to meet. Instead of positive growth documented by these studies, we found an overall fall of green productivity during the period 1998–2015. Only ML indexes of Beijing, Shanghai, Tianjin and Heilongjiang were greater than one. For other provinces, there was no evidence showing that their GTFP was improving in the period of 1998–2015.

The absolute values of TFP and GTFP indexes estimated by different studies may be not comparable because of variances in methods, inputs and outputs choosing, and studied time periods. Nevertheless, the rankings of provinces based on these indexes can provide us knowledge about their relative performances which local governments care more about. Rankings of provinces according to GDPr, Mb, and MLb respectively are presented in Fig. 3.

If looking into only GDP growth, Inner Mongolia, Tianjin, Chongqing, Jiangsu and Shaanxi, went to top 5. The bottom 5 were Xinjiang, Heilongjiang, Yunnan, Gansu and Hebei. Shanghai and Beijing ranked 6^{th} and 8^{th} from the bottom. Nevertheless, under the TFP measure, results were totally different. Shanghai ranked first who ranked last 6th in GDP growth. The last one was Inner Mongolia who ranked first in GDP growth. Therefore, indicator of GDP growth only cannot reflect whether the growth comes from efficiency advancement or simply extensive usage of resources which is inefficient and unsustainable.

Including the assessment of environmental impact of growth, rankings among provinces changed again. Beijing, Shanghai, Tianjin and Heilongjiang stood out with ML indexes greater than unity, i.e., their green productivity efficiency improved. Fig. 4(a–c) show the maps of GDP growth, TFP growth and GTFP growth respectively, where darker colors represent larger growth rates. The spatial distribution pattern of the three growth indexes differed. Fig. 4(d) displays the changes from GDP growth ranking to GTFP growth ranking, with blue for higher position and red for lower position. Performance of Beijing, Shanghai, Heilongjiang, Gansu, Liaoning and Hunan were underscored under the GDP growth evaluation system, while growth of Fujian, Qinghai, Hubei, Inner Mongolia, Jiangsu and Shaanxi were most overestimated.

Discrepancy between TFP and GTFP enlightens how much the economic development relies on the consumption of natural resources and environment capacity (Fig. 4e). Consist with previous studies, we found Shanghai occupied the leading position in both TFP growth and GTFP growth. Guangdong ranking fourth in TFP growth still performed well after considering environmental efficiency. Compared to rankings in TFP growth, Beijing, Tianjin, Heilongjiang, and Hunan moved upward to top five in GTFP growth,

Table 5
Technology change component index (MLTECH) for provinces, 1998–2015.

Province	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Beijing	1.11*	1.17*	1.12*	1.10	1.13*	1.19*	1.09	1.07	1.11	1.12*	1.11	1.03	0.99	1.07	1.22*	1.02	1.05	1.11
Tianjin	1.05	1.20*	0.94	0.98	1.06*	1.09*	1.06	0.96	1.10*	1.09*	1.07	1.07	0.99	1.05	1.08	1.07	1.09	0.96
Hebei	0.98	1.01	1.01	1.01	1.01	1.02	1.03	1.00	1.00	0.99	0.96	0.98	1.01	1.01	1.02	1.03	1.02	1.00
Shanxi	1.00	1.01	1.03	1.03	1.04	1.04	1.07	1.03	0.99	1.00	0.97	0.98	1.00	1.03	0.99	1.01	1.00	1.00
Inner Mongolia	1.03	1.01	1.03	1.04	1.03	1.02	1.07	1.04	1.04	1.06	0.99	1.01	0.93	1.01	1.02	0.99	1.02	1.01
Liaoning	1.01	1.01	1.02	0.99	1.01	1.01	1.01	1.00	1.01	0.99	0.94	0.99	1.01	0.98	1.03	1.03	1.00	1.00
Jilin	1.04	1.02	1.02	1.02	1.00	1.02	1.04	0.98	1.00	1.03	1.01	1.05	0.94	0.99	1.06	0.98	1.01	0.95
Heilongjiang	1.04	1.04	1.01	1.05	1.03	1.04	1.04	1.04	1.03	1.01	0.99	1.01	0.98	1.04	1.06	1.01	1.00	1.00
Shanghai	1.20*	1.06	1.04	1.06	1.04	1.08*	1.08	1.08	1.16*	1.14*	1.00	1.04	0.98	1.03	1.06	1.04	1.05	0.93
Jiangsu	1.03	.	.	0.98	.	.	1.04	1.01	1.04	1.02	0.99	0.98	0.96	0.98	0.96	0.96	0.97	0.91*
Zhejiang	0.95	0.98	1.01	0.99	1.03	1.03	1.02	1.04	1.04	1.01	1.02	1.04	0.99	1.02	1.07	1.04	1.02	1.01
Anhui	1.03	1.01	1.00	1.00	1.00	1.02	1.03	1.00	1.01	1.01	0.99	0.97	0.97	0.98	0.97	0.97	1.01	0.97
Fujian	0.95	0.98	0.93*	0.99	1.00	1.03	1.00	0.99	1.07	0.95	1.04	1.12	0.87*	1.02	1.06	1.00	1.00	0.99
Jiangxi	1.03	0.99	0.99	1.00	0.99	0.99	1.00	0.99	1.02	1.01	1.00	1.01	0.96	0.98	1.01	1.02	1.05	0.99
Shandong	1.07*	1.06*	1.02	1.03	1.05*	1.02	1.03	1.00	1.00	1.01	0.98	1.00	0.93	1.02	1.07	1.01	1.01	0.99
Henan	1.02	1.01	1.00	1.00	0.99	1.01	1.03	1.00	1.01	0.99	1.01	1.04	0.96	0.95	1.05	1.00	1.00	0.99
Hubei	0.96	0.98	0.99	0.97	0.96	1.00	0.99	0.99	0.99	1.00	1.00	.	.	0.97	0.96	0.99	1.01	0.96
Hunan	1.05	0.99	1.01	1.01	1.01	1.04	1.00	1.03	1.09*	0.97	1.03	1.06	0.92	1.03	1.06	1.01	1.04	1.00
Guangdong	1.00	1.00	1.03	1.02	1.03	1.05	1.04	1.04	1.10	1.00	0.98	0.95	0.95	0.96	1.01	1.02	1.05	0.99
Guangxi	1.01	1.01	1.00	0.99	1.00	1.01	0.99	1.00	1.03	0.98	1.04	1.02	1.00	0.94	0.99	1.02	1.01	0.99
Hainan	1.07	1.05	0.88*	1.11	0.96	1.09*	1.00	0.99	1.02	1.07	0.93	1.10	1.04	0.95	1.03	1.03	0.98	0.99
Chongqing	1.03	0.98	0.99	1.03	1.01	1.03	0.95	1.03	1.01	0.97	1.03	0.97	1.02	1.07	1.09	1.00	1.03	0.98
Sichuan	1.02	0.99	1.00	0.97	0.98	1.03	1.02	1.01	1.04	1.00	0.99	1.00	0.98	0.99	0.99	1.03	1.04	1.04
Guizhou	1.00	1.02	1.02	1.01	1.05*	1.04	1.05	1.06	1.06	1.05	1.02	0.99	1.01	0.97	1.00	1.02	0.98	1.01
Yunnan	1.02	0.98	0.97	1.00	1.01	1.01	1.00	1.01	0.99	0.99	1.01	0.99	0.97	0.97	1.02	1.00	0.99	0.96
Shaanxi	0.99	1.05*	1.00	1.00	1.00	1.02	1.02	1.02	1.02	1.02	0.95	1.02	0.96	1.01	1.01	1.02	1.01	0.95
Gansu	1.03	1.07*	1.06	1.06	1.00	1.01	1.10*	0.99	0.97	0.97	0.95	0.97	0.97	0.97	0.97	0.97	0.99	0.95
Qinghai	1.06*	1.07	0.98	1.02	1.03	1.01	1.01	0.97	0.97	0.98	0.99	0.95	0.96	1.00	0.98	0.99	1.01	1.00
Ningxia	0.98	1.01	0.97	1.00	1.00	1.02	1.03	0.98	1.01	0.98	1.00	0.99	0.92	1.01	1.00	0.99	1.00	0.99
Xinjiang	1.01	1.07	1.01	1.01	1.01	1.00	1.02	1.02	0.99	1.00	1.00	0.98	0.95	0.99	0.99	0.98	0.99	0.99

Note: *Significant from unity at 95% confident level.

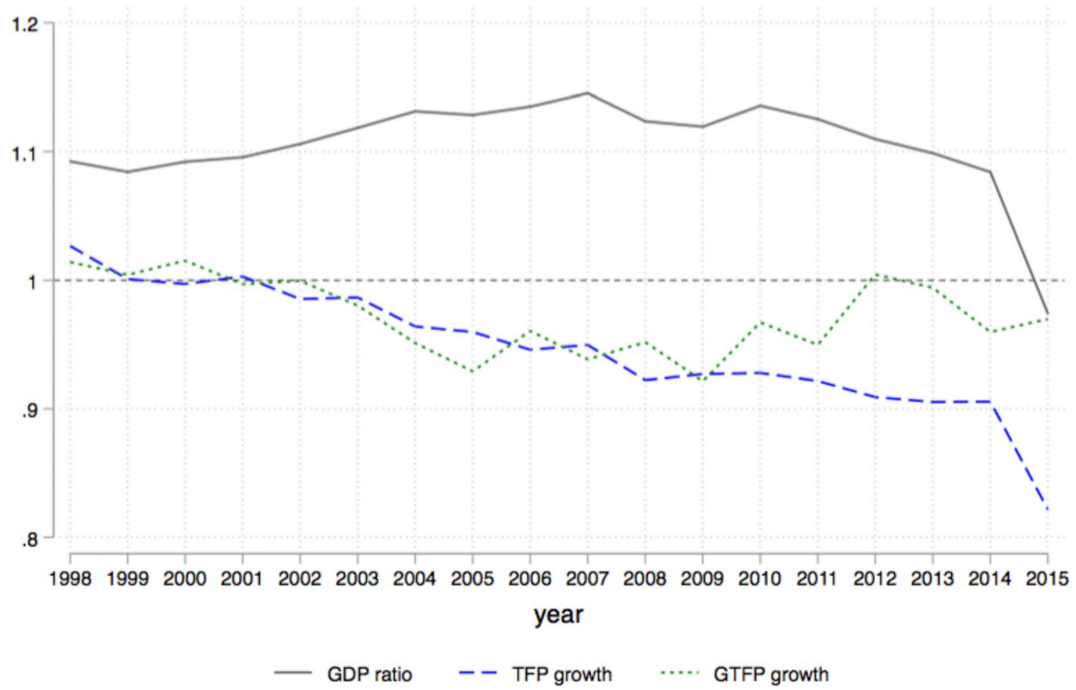

Fig. 2. Time trends of national aggregated GDP, TFP and GTFP growth, 1998–2015.
Notes: GDP ratio refers the ratio of real GDP this year over real GDP last year measured at 1978 constant price. TFP growth is indicated by Malmquist index, and GTFP growth is indicated by Malmquist-Luenburger index with emissions of industrial waste gas, water and solid as undesirable outputs. Both TFP growth and GTFP growth indexes are bias corrected by bootstrapping procedure.

Table 6
Average GDP ratio, Malmquist index and Malmquist-Luenberger index over 1998–2015, by province.

Province	GDP ratio	Malmquist index	Malmquist-Luenburger index
Beijing	1.10	0.94	1.12
Tianjin	1.13	0.97	1.05
Hebei	1.10	0.94	0.94
Shanxi	1.10	0.93	0.95
Inner Mongolia	1.13	0.91	0.96
Liaoning	1.10	0.94	0.98
Jilin	1.11	0.92	0.97
Heilongjiang	1.09	0.96	1.01
Shanghai	1.10	1.02	1.07
Jiangsu	1.11	0.96	0.95
Zhejiang	1.10	0.94	0.97
Anhui	1.10	0.97	0.96
Fujian	1.11	0.94	0.93
Jiangxi	1.11	0.97	0.94
Shandong	1.11	0.96	0.98
Henan	1.10	0.93	0.94
Hubei	1.11	0.94	0.92
Hunan	1.11	0.96	1.00
Guangdong	1.11	0.97	0.99
Guangxi	1.11	0.92	0.96
Hainan	1.10	0.97	0.96
Chongqing	1.11	0.96	0.98
Sichuan	1.11	0.98	0.99
Guizhou	1.11	0.96	0.99
Yunnan	1.09	0.94	0.94
Shaanxi	1.11	0.95	0.96
Gansu	1.10	0.95	0.96
Qinghai	1.11	0.92	0.94
Ningxia	1.10	0.91	0.95
Xinjiang	1.09	0.93	0.92
Total mean	1.11	0.95	0.97

Notes: GDP ratio refers the ratio of real GDP this year over real GDP last year measured at 1978 constant price. Malmquist index and Malmquist-Luenburger index are both bias corrected after bootstrapping procedure.

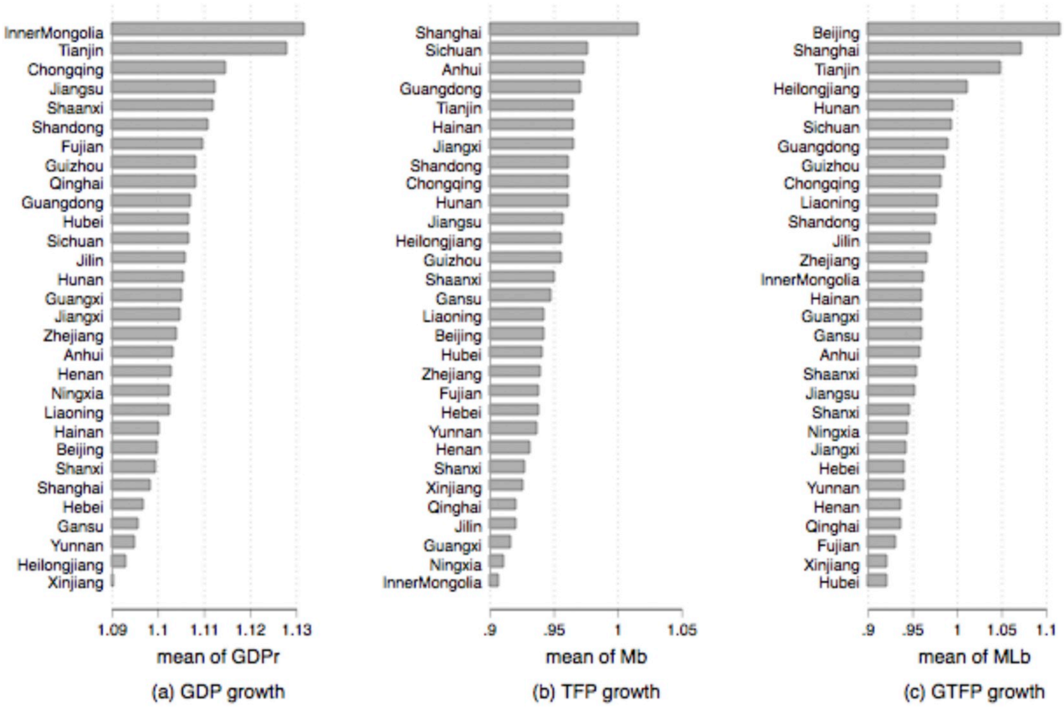

Fig. 3. Rankings of provinces by average GDP, TFP and GTFP growth over 1998–2015.

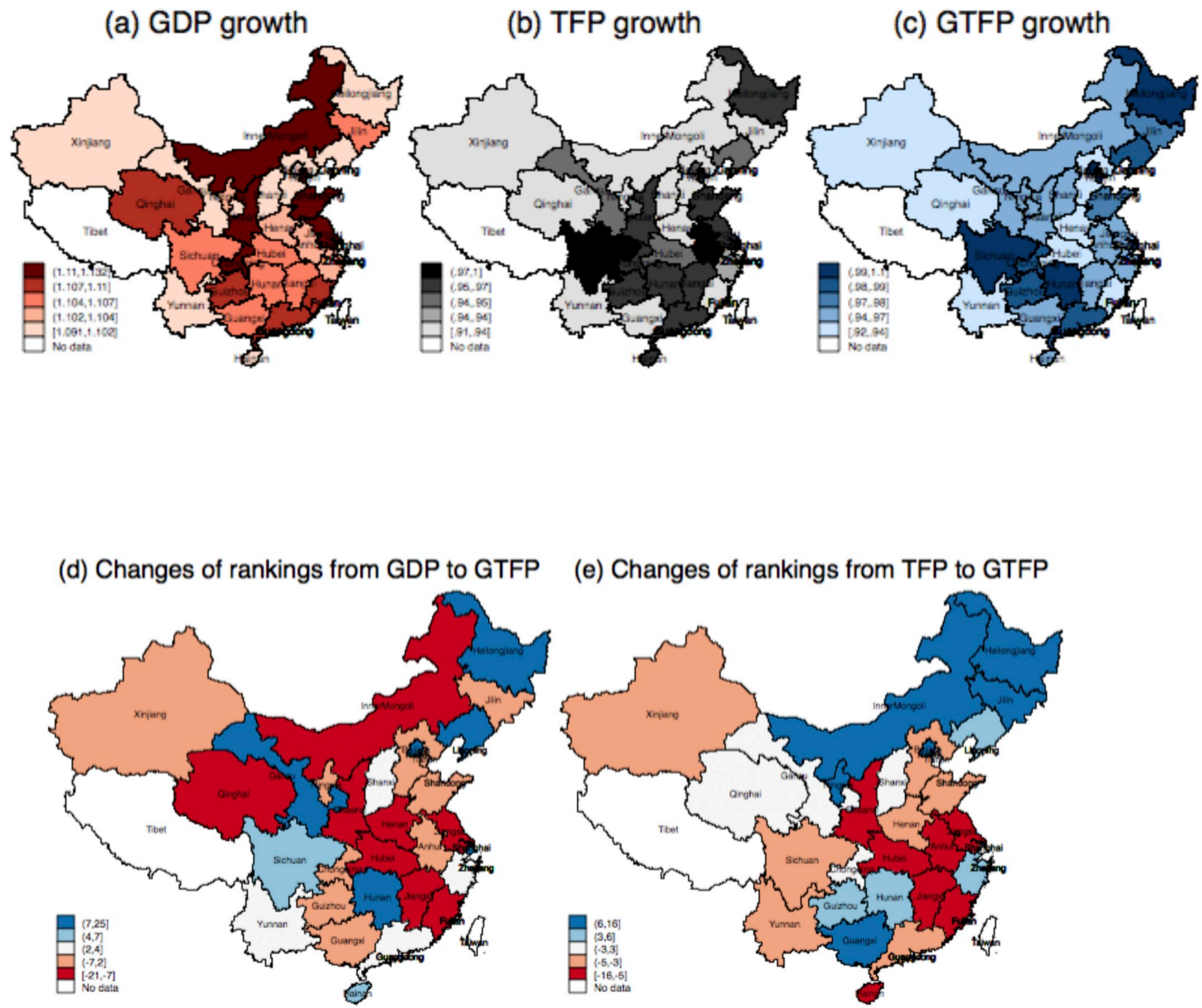

Fig. 4. Divergence in spatial distribution of GDP, TFP and GTFP growth.
Notes: Blue stands for the rise of ranking based on GTFP growth relative to that based on GDP(or TFP) growth, and red stands for the drop.

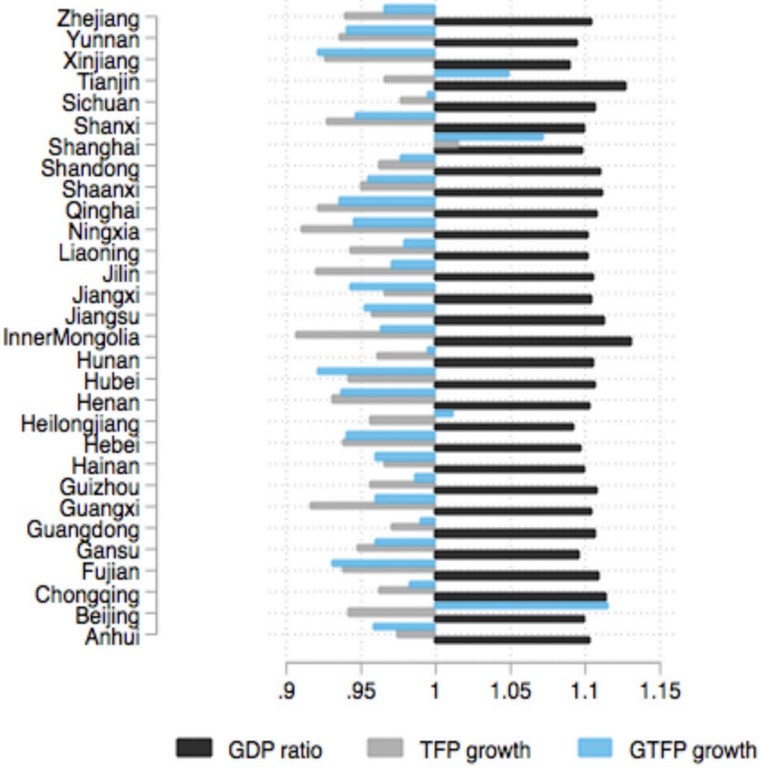

Fig. 5. Evaluation of growth quality for Chinese provinces.

and Jilin and Inner Mongolia progressed from the bottom to the middle positions. Significant drops of grades were seen in Anhui, Hainan, Hubei, Fujian, Hebei, Xinjiang and Jiangsu etc. It was formerly believed that the eastern region had both the highest TFP and the highest GTFP growth, followed by the middle region and the western region (Hu et al., 2008; Wang et al., 2010). Except Shanghai, this was not true in our study. Most provinces in the east experienced ranking declines turning from TFP growth to GTFP growth, and GTFP growth of Jiangsu and Zhejiang were not outstanding as expected. Instead, provinces in the northeast and middle region, such as Heilongjiang, Hunan, Guizhou, Sichuan, outperformed Jiangsu, Zhejiang and Fujian in the east in GTFP growth.

Based on comparisons of GDP growth, TFP index and GTFP index, the growth quality of a given province can be approximately inferred. In Fig. 5, the bars show how much indexes deviate from one. The longer the bars to the left are, the more the GDP or efficiencies are reduced. The longer the bars to the right are, the more the GDP or efficiencies are increased. The relative length of bars for TFP and GTFP growth reveals whether production efficiency of a province improved or worsened after accounting environmental externalities. To illustrate how these three bars together help evaluate the economic development quality clearly, two opposite examples are Inner Mongolia and Shanghai. With both long bars for GDP growth to the right and long bars for efficiency changes to the left, economy of Inner Mongolia was growing fast in an unsustainable way at the expense of inefficiency and waste of resources. With long bars for GDP growth and efficiency changes simultaneously to the right, as well as longer bar for GTFP growth than TFP growth, Shanghai is developing at the most efficient and green way.

4.2.3. Relationship between TFP growth and GTFP growth

In the comparison among provinces in Section 4.2.2, it is notable that the productivity measures for some provinces got better while some got worse after introducing undesirable outputs. Relative performance of traditional TFP growth and GTFP growth indexes are of great importance to help identify the role of environmental inefficiency in the general inefficiency or how much GTFP growth is driven by TFP growth. Therefore, relationship between TFP growth and GTFP growth is explored in more depth in this section.

To examine the correlation between TFP growth and GTFP growth, Fig. 6 scatters measures of Mb indexes (horizontal axis) and MLb indexes (vertical axis) and for some given provinces grouped by geological region for each year during 1998–2015 Lines of Mb = 1 and MLb = 1 (red dashed lines) split the graph into four blocks: right-top block where both TFP and GTFP increase, left-top block where TFP decreases but GTFP increases, left-bottom block where both TFP and GTFP decrease, right-bottom block where TFP increases but GTFP decrease. The 45-degree line of Mb = MLb (grey dotted line) also divides two parts: above the line, GTFP growth greater than TFP growth, suggesting positive contribution of environmental factors in GTFP; below the line, GTFP growth slower than TFP growth, implying negative role of environmental efficiency.

Starting with Jing-Jin-Ji Metropolitan Region that consists of capital city Beijing, Tianjin city and Hebei province (Fig. 6a), despite their TFP growth were similar and negative except some years for Tianjin, there were distinct differences in development

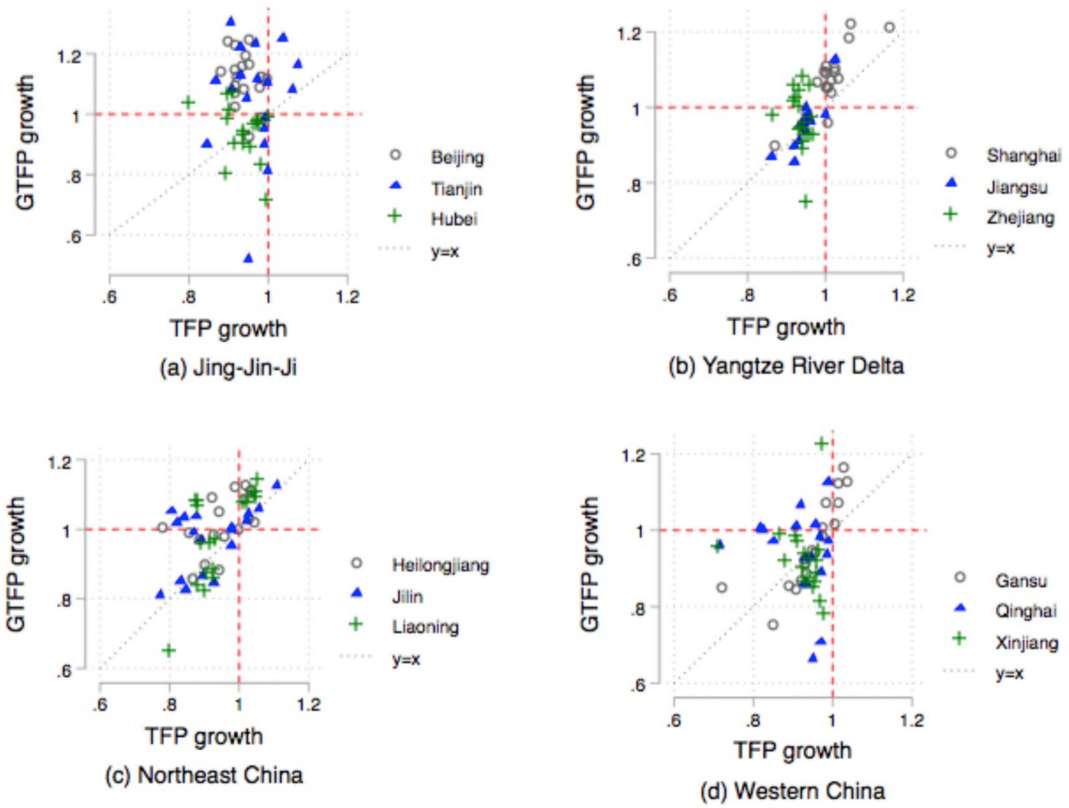

Fig. 6. Comparison of TFP and GTFP growth by region.
Notes: (1) Lines of Mb = 1 and MLb = 1 (red dashed lines) split the graph into four blocks: right-top block where both TFP and GTFP increase, left-top block where TFP decreases but GTFP increases, left-bottom block where both TFP and GTFP decrease, right-bottom block where TFP increases but GTFP decrease. (2) The 45-degree line of Mb = MLb (grey dotted line) divides two parts: above the line, GTFP growth greater than TFP growth, suggesting positive contribution of environmental factors in GTFP; below the line, GTFP growth slower than TFP growth, implying negative role of environmental efficiency.

pattern for them. Observations of Beijing fell mostly within left-top block, while those of Hebei within left-bottom block. Besides, most observations of Hebei were found below the 45-degree line, while those for Beijing and Tianjin were above. That is to say, the traditional productivity was decreasing in Jing-Jin-Ji, but Beijing and Tianjin were developing more and more 'green', yet economic growth of Hebei province was getting more and more environmentally intense.

Shanghai, Jiangsu and Zhejiang constitute the most developed Yangtze River Delta metropolitan region in eastern China (Fig. 6b). Observations of Shanghai were mainly within the right-top block and above the 45-degree line. This suggests that traditional economic productivity was constantly increasing in Shanghai, and together with outstanding environmental performance, contributed to the persistently growing green productivity. Differently, Zhejiang and Jiangsu provinces experienced negative TFP growth in most years. GTFP growth rates varied around zero, but generally outperformed TFP growth, implying negative growth in green productivity could be driven by TFP declines.

Three provinces in Northeast China did not show much difference in the productivity changes (Fig. 6c), with observations distributed in all blocks excluding the one with positive TFP growth and negative GTFP growth, and above the line where GTFP growth exceeds TFP growth. Although standard economic productivity in Northeast China went through recession in most cases, the environmental performance actually played a positive role in the more comprehensive green productivity index.

A completely different relationship between TFP and GTFP growth was uncovered in three examples of provinces in the west of China (Fig. 6d). Concentrated in the left-bottom block and below the 45-degree line, Gansu, Qinghai and Xinjiang not only underwent decrease in TFP, but also environmental degradation that resulted in poorer GTFP. It is worrying that economic growth in the western China was achieved inefficiently, and from bad to worse, at sacrifice of natural resources and environment.

4.3. Comparison of growth quality in Beijing, Shanghai and Hebei

Notwithstanding a general decreasing trend in TFP and GTFP in China, Beijing and Shanghai were two attractive exceptions enjoying continuous improvement in green productivity. Even in the ML measures within the secondary industry (Appendix 2), Beijing and Shanghai also outstood in GTFP growth. Also, how growth of economies within a metropolitan region was related to each other

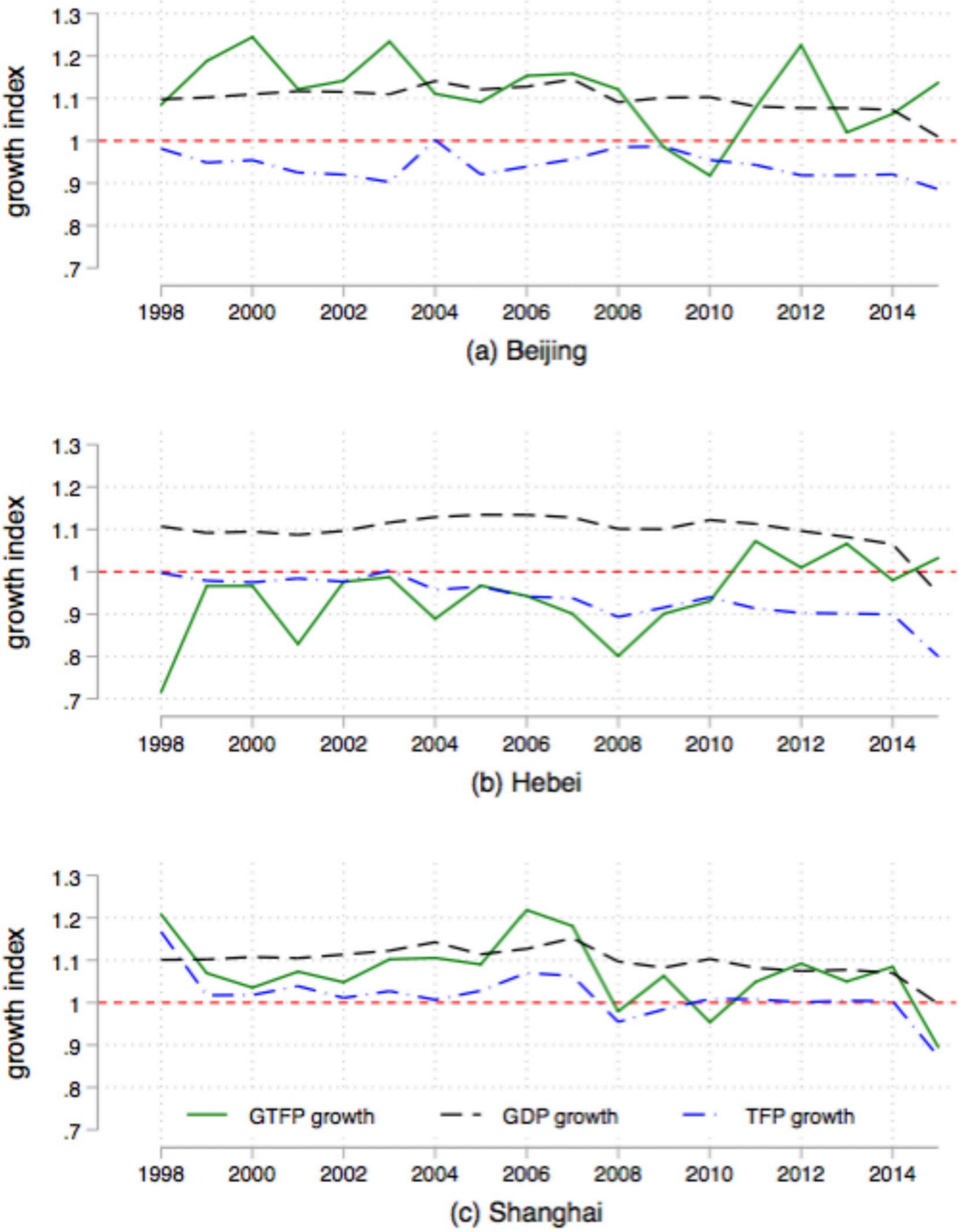

Fig. 7. Examples of different growth quality: Trends comparison of GTFP, GDP and TFP growth among Beijing, Hebei and Shanghai, 1998–2015.

indicated by Fig. 6 was interesting. Hebei, as a neighbor province of the capital city, yet presented an opposite growth direction to Beijing in terms of green productivity. In this section, we highlight the assessment of quality of growth in Beijing, Shanghai and Hebei as three different and attractive examples in rich details, and provide some potential reasons behind their divergent performances.

Fig. 7 depicts time trends of indices of GDP growth, TFP growth and GTFP growth for Beijing, Hebei and Shanghai. First, the GDP ratios of this year over last year for the three cities and province were all around 1.1, corresponding to 10% growth rate, and had similar trends. Second, TFP growth index was always no greater than unity in Beijing and Hebei, but over unity in Shanghai for most years. And the downward trend in TFP growth was obvious in Hebei, especially from 2003 to 2008, indicating that TFP decreased more and more quickly. Third, GTFP was growing in Beijing and Shanghai, at rates comparable to GDP growth and greater than TFP growth, while in Hebei, GTFP kept falling until 2011, at rates greater than TFP degradation.

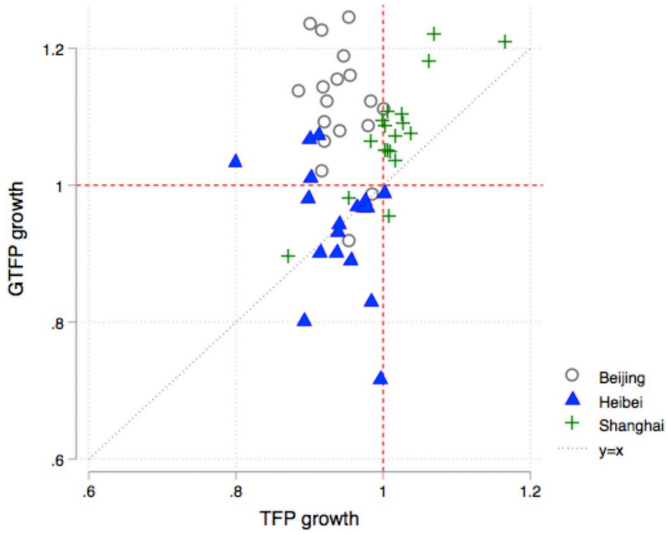

Fig. 8. Examples of different growth quality: Correlation between TFP vs GTFP growth for Beijing, Hebei and Shanghai, 1998–2015.

To detect more clearly how TFP and GTFP growth related, Fig. 8 scatters all estimates of GTFP growth index against TFP growth index for the three economies in the same way as described in Fig. 6. Observations were distinctly separately located, with Beijing in left-top, Shanghai in right-top above the 45-degree line, and Hebei in left-bottom and basically under the 45-degree line. TFP declines could not explain all the drops seen in GTFP in Hebei, inefficiency regarding undesirable outputs production expanded definitely. In addition, observations for Shanghai were close to the line that GTFP growth equals TFP growth, and it could be noticed also from Fig. 7(c), the GTFP and TFP growth moved together in Shanghai. The drop of GTFP in 2008 could be largely driven by TFP decrease. The three totally different modes Beijing, Hebei and Shanghai presented were of great interest, and reasons underlying this could be multiple. We explore here from some narrative evidence and try to provide some intuitive explanation.

First, industrial structure determines to a large extent how economic growth is realized. Beijing and Shanghai are two largest megacities in China, serving as political and cultural, financial and trade centers, thus developing more towards the tertiary industry (service sector) instead of secondary industry (manufacturing sector). As shown in Fig. 9, the service industry share in GDP kept expanding in Beijing, from a high level of 60% in 1997 to nearly 80% in 2014, with the secondary industry share shrinking all the way. The tertiary industry in Shanghai accounted for a slightly smaller share than Beijing, but still grew from less than 50% in 1997 to 60% in 2014, which is a large proportion. The large and increasing service industry along with small and decreasing secondary industry should be responsible for the improvement in GTFP in Beijing and Shanghai. To the contrary, Hebei is an important industrial province possessing many polluted industries, such as coal, steel, iron, chemical production, petroleum, power, and ceramics. The share of secondary industry in 1997 was 49% and went highest in 2008 to 54.3%, which partly explained the negative growth in GTFP and downward growth trend before 2008. Service industry took up a much lower share around 30% and increased after 2008 moderately in recent years. This is consistent with the upward trend in GTFP growth in Hebei since 2008 (Fig. 7b).

Furthermore, the variation of industry composition over time is closely associated with development and environmental protection strategy of local governments. With unprecedented development that earned them opportunities to hold major international events, and at the same time posed unprecedented burden on environment, Beijing and Shanghai faced special challenges in the past years. While Hebei is also special, as a large neighbor surrounding Beijing geologically and influencing Beijing both environmentally and economically.

Since the successful bid for 2008 Olympics Games in 2001, Beijing had made great efforts on reducing pollution emission to ensure air quality during the event, which brought real and substantial impacts on its industries and economy.[12] On the one hand, polluting factories were moved, adjusted, or closed. During this period, 144 polluting enterprises in the urban area were relocated out of Beijing and many to neighbor provinces, which was supported by the observed significant decline in secondary industry in Beijing but increase in Hebei before 2008 (Fig. 9). In the central city, 16,000 coal-fired boilers with a relatively small capacity were converted into natural gas fueled, while more than 400 coal-fired large boilers as well as all the 4 coal-fired power plants installed desulfurization, dedusting and denitrification treatment. In the suburbs, all polluting cement, sand, brick factories, and all chemical enterprises were shut down, and so were the coal-fired generating units in power plants. On the other hand, eighteen stringent local emission regulations involving many pollutants and industries were set up to promote clean technology and industry upgrade. It is not surprising to find GTFP improvement in Beijing, given these changes taken place in energy, industry and technology.

However, measures to reduce pollution in Hebei for the Olympic Games were mostly temporary, rather than structural. To control the pollution transport from neighborhood and to curb the increase in pollution concentration before the opening ceremony, Beijing,

[12] Data below describing measures of emission controls is summarized from news published by Beijing Ministry of Environmental Protection, available at http://www.zhb.gov.cn in Chinese language.

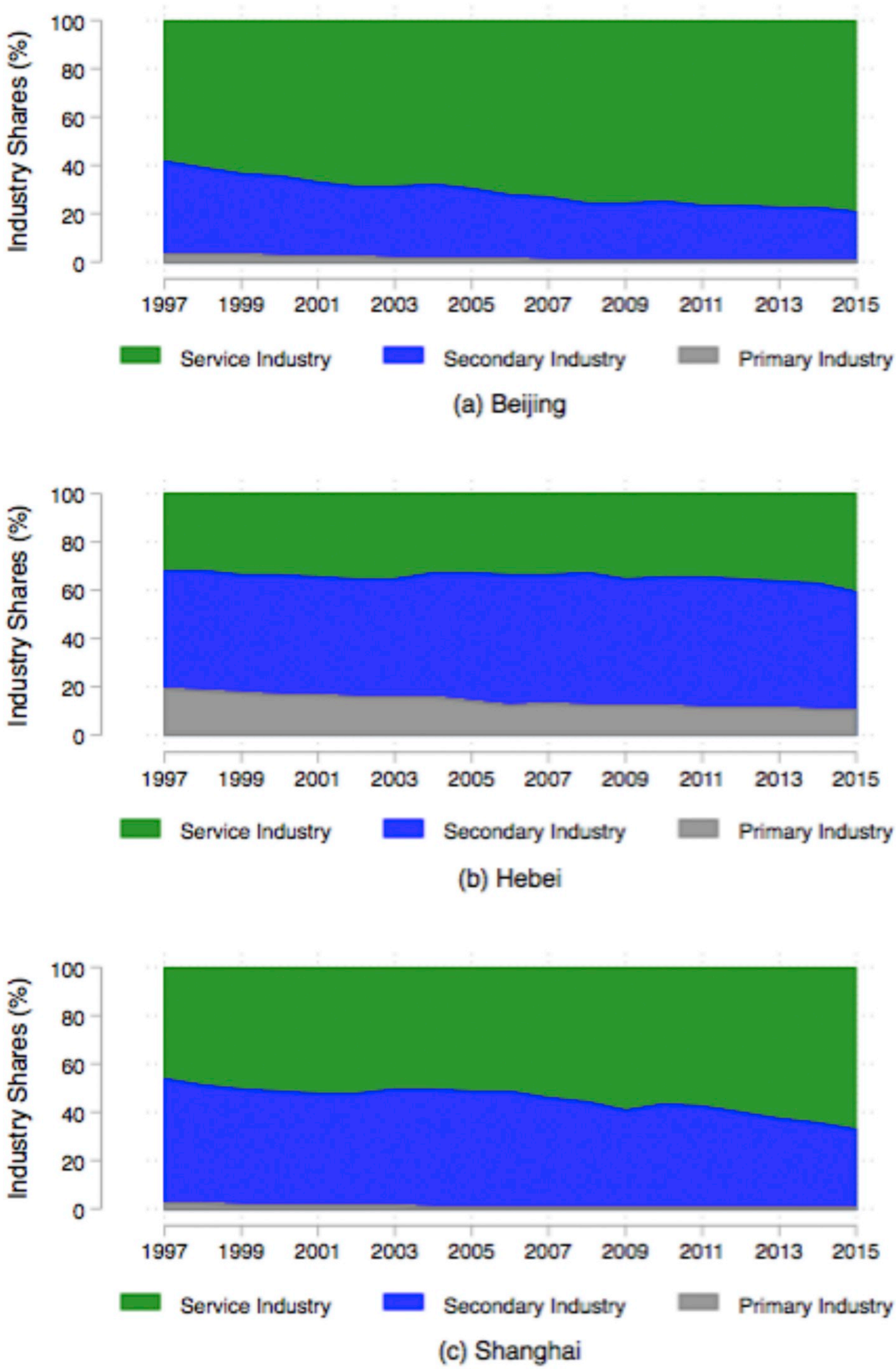

Fig. 9. Industrial structure changes from 1997 to 2015 in Beijing, Hebei and Shanghai.

Tianjin, and Hebei jointly launched a regional emergency plan, and imposed production suspension on more than 1000 enterprises. Acceptance of polluting industries and no long-term pollution reduction strategy, led to environment degradation inferred by lower GTFP growth indexes than TFP growth indexes in Hebei. Interestingly, after 2008, GTFP growth dramatically dropped and became negative in 2009 in Beijing, which might indicate a rebound effect after stringent environmental regulation. By contrast, a significant increasing trend in GTFP growth was captured in Hebei, and became positive in 2011, providing a signal that somehow environmental efficiency attracted more attention in Hebei ever since.

For Shanghai, it applied for the 2010 World Expo from 2000, and succeeded in 2002. Taking this event as an opportunity, Shanghai implemented rounds of three-year action plans for environmental protection beginning at 2000, which were comprehensive projects targeting at water pollution, wastes treatment and air pollution in the long run. Investment in environmental protection increased at an average rate of 18.0% during the five years before the event, which was greater than the GDP growth rate 12.8% at the same period (Shanghai Ministry of Environmental Protection, 2009).

Similar to Beijing, adjustments in industry and energy structure were also the main strategies for Shanghai to improve environmental performance, but with some differences. By closing and merging high-polluting industries and promoting high-tech industries as well as circular economy, Shanghai strategically directed industry development from relying on resource consumption towards relying on technological progress. In addition to reducing coal share in the energy consumption by 14% from 2000 to 2007, Shanghai was also committed to improving energy efficiency, with 1) strict entry restriction on new projects, 2) restructuring or removing existing high energy consumption and pollution production capacity, and 3) constructing systems that favor energy-saving technology and products. Local environmental regulations stricter than national standards were also developed in Shanghai, covering air, water, marine, solid waste, noise, soil pollution and so on. Compared to Beijing, though shrinking, second industry still played a critical role in Shanghai's economic growth (Fig. 9). But with more stress on energy efficiency and promotion energy-saving technology, Shanghai was able to achieve growth in both TFP and GTFP due to the commonly correlated energy inputs and other inputs.

4.4. Empirical evidence of factors affecting growth quality

Special international events provide Beijing and Shanghai junctures to enhance environmental protection through various aspects, such as industrial structures, environmental regulation, high-tech industry promotion. In this section, we try to generalize the analysis and provide some empirical evidence on the factors that could explain different patterns of growth quality revealed by the Malmquist index and ML index across Chinese provinces.

As environmental regulations are hard to quantify accurately at provincial level, we focus on the industrial structures and technology development. We obtain shares of primary industry, secondary industry, and tertiary industry in GDP for the 30 provinces during 1997–2015, from the China Statistical Yearbook. We also collect R&D expenditures by province, 1998–2015, from China Statistical Yearbook on Science and Technology to measure the investment in technology.[13] Percentages of R&D expenditures in GDP are calculated to better represent the efforts local governments devote on technology development and advancement.

Distinct from static indexes, Malmquist index and ML index both measure dynamic productivity changes, specifically, using last year as the base year in this study. Therefore, we use the first order differences of the industrial structure and R&D percentage to explain the corresponding change in TFP and GTFP.

We estimate the impacts of three industry shares and R&D devotion on productivity changes following the specification:

$$y_{it} = \beta_1 AgriShareChange_{it} + \beta_2 ServiceShareChange_{it} + \beta_3 R\&DShareChange_{it} + \tau_t + \varepsilon_{it} \tag{12}$$

Where y_{it} is index for TFP growth rate or GTFP growth rate (in %) for province i in year t based on indexes constructed in this study; $AgriShareChange_{it}$ is the difference of agriculture sector share in GDP for province i between year t and year $t-1$; By analogy, $ServiceShareChange_{it}$ is the difference of service sector share in GDP for province i between year t and year $t-1$, and $R\&DShareChange_{it}$ is the difference of R&D expenditures percentage in GDP for province i between year t and year $t-1$; τ_t stands for year fixed effects; ε_{it} is the error term.

Because the sum of changes in three industry sector shares equals zero for a province in a given year, which make them perfectly collinear, we omit the second sector, i.e., the share change of secondary industry sector. The coefficients of our interest, β_1, should be interpreted as, holding service sector share constant, if secondary industry shrink by 1% and the primary industry increase by 1%, the productivity growth rate would change by β_1%. Similarly, β_2 captures the impact of converting secondary industry share to the tertiary industry by one unit on the productivity growth rate, keeping agriculture sector share constant.

We include the year fixed effects to control unobservable common shocks in the same year for all provinces. Because the variables are actually in the form of first order difference, and models of individual fixed effects in panel data are equivalent to those of first order difference (the time-invariant factors for the individual have already been differenced), there is no need to involve province fixed effects again.

Table 7 report the regression results for ML and Malmquist indexes and their corresponding decompositions of efficiency change and technology change respectively. According to column (1)-(3), reduction in the secondary industry share is positively related to GTFP growth, especially when the share goes to the service sector. Transforming 1% secondary industry to service industry, would enhance GTFP growth rate by 0.5%, through both efficiency improvement and statistically significant technology progress. Despite that most of coefficients are insignificant, coefficients of service sector and their t-statistics are larger in magnitude than those of agriculture sector.

While for TFP growth in column (4)-(6), industrial structure has much weaker impacts in general. Expansions of service sector contribute little to the TFP growth rates, with much smaller magnitudes and larger variances of coefficients. It might suggest service sector requires labor and capital input as intensively as secondary industry to produce GDP. Interestingly, coefficients of agriculture sector show similar patterns as those for GTFP growth. Increases in secondary industry share from primary industry, holding service sector fixed, would decrease TFP growth rates through technology regress.

R&D expenditures play important roles in productivity based on our estimation. Expand R&D investments by 1% in GDP would significantly raise TFP growth rates by 4.5%, 2.98% from efficiency improvement and 1.75% from technological progress. Though less significantly, coefficients of R&D expenditures are also with same signs and similar magnitudes for GTFP growth. R&D

[13] The indicator of intramural R&D expenditures was first available in 1998.

Table 7
Effects of industrial structure and R&D expenditure on GTFP, TFP growth.

	(1)	(2)	(3)	(4)	(5)	(6)
	ML	MLEFFCH	MLTECH	Malmquist	MEFFCH	MTECH
Agriculture Sector (%)	0.2572	−0.0316	0.2680	0.1866	−0.0585	0.2348*
	(0.378)	(−0.0613)	(1.068)	(0.688)	(−0.312)	(1.669)
Service Sector (%)	0.5355	0.2863	0.2217*	0.0437	−0.0388	0.0728
	(1.559)	(1.056)	(1.882)	(0.313)	(−0.368)	(1.090)
R&D/GDP (%)	5.2015	2.7809	2.5760	4.5178**	2.9801**	1.7512*
	(1.034)	(0.777)	(1.186)	(2.336)	(2.098)	(1.851)
Observations	504	504	504	510	510	510

Notes: Each column presents results of a separate regression for an index indicated by the column title; Explained variables of indexes are deducted by 1 and multiplied by 100, thus measuring growth rates in the unit of %; Explanatory variables are in the form of first order difference, documenting the changes relative to previous year; For all the regressions, year fixed effects are controlled; t statistics in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

expenditures are positively related to GTFP growth rates, through both efficiency and technological shift. The differences in the statistical significance also make sense as we use the total R&D expenditures rather than R&D in environmental protection.

By exploiting the variation of industrial structure and R&D investment across Chinese provinces, our analysis suggests that shrinks of secondary industry share and expansions in service sector would help faster GTFP growth, while have little effects on TFP growth. Increasing R&D expenditures portion would advance GTFP and TFP growth, through both efficiency and technology improvement.

5. Conclusion

Using nonparametric method, in this paper we estimated the green total factor productivity indexes incorporating environmental variables to examine quality of economic growth for provinces in China, during the period of 1998–2015. Bootstrapping method was implemented for correcting estimation bias and testing significance of estimates. Further decomposing the GTFP index into efficiency change index and technological index, we found that changes in GTFP resulted most from efficiency changes rather than technological progress for most provinces.

We also compared results of the GTFP indexes with the traditional TFP indexes and the rates of GDP growth. The comparison indicated that the three indexes demonstrated quite different time trends. Despite GDP was growing fast, TFP and GTFP showed no positive growth for most provinces in most years, and a general descending trend of growth rates. But the national average GTFP growth rates rebounded after 2007, potentially resulted from the redirection of development by central government in pollution reduction and energy saving since the eleventh five-year plan (2006–2010).

Although national average GTFP growth displayed similar trend as TFP growth, GTFP indexes had revealed different quality of growth across provinces as TFP indexes did. Provincial ranking based on GTFP indexes significantly differed from what was produced by the GDP growth rates or the traditional TFP indexes. TFP indexes indicate whether the economic growth comes from efficiency advancement or not, but cannot disclose whether it is based on polluting the environment or not. Provinces with relatively high TFP growth rates, e.g., Anhui and Hainan, not necessarily had high production efficiencies once considering environmental damages. Changes in TFP can contribute to those in GTFP, but some provinces performed better after accounting environmental factors, such as provinces in the northeast of China, while some performed worse, e.g., Gansu, Qinghai, Xinjiang in Western China.

Outstanding and continuous GTFP improvement occurred only in Beijing and Shanghai, which was not that surprising due to their serious regulations and policies targeting energy and industry restructure to protect environment and ensure environment quality. Improvement in GTFP in Beijing was achieved more through compulsory controls compared to Shanghai, such as removing and shutting down polluting industries, strict and direct regulations on pollution emissions, which was supported by decreasing TFP. While by taking advantage of technology advancement and improving energy efficiency, developing secondary and service industry at the same time, Shanghai progressed in both TFP and GTFP.

Our empirical analysis exploiting variations in industrial structure and R&D investment across Chinese provinces suggest that, increase in service sector share and decrease in secondary industry positively contribute to GTFP growth rate, and higher percentage of R&D expenditure in GDP would help drive up both GTFP growth and TFP growth.

The GTFP is a comprehensive index of growth quality addressing efficiency and environmental sustainability at the same time. More importantly, estimating GTFP with nonparametric method is a theoretically sound exercise, which is also proved by our reasonable results consistent with reality. In practice, it can be achieved with data published in statistics books, therefore it is a simple and low-cost way of estimation, with a much lower cost than the work of Green GDP. It is yet a perfect substitute for Green GDP. With reliable data, GTFP index can be used as an effective and low-cost instrument for gauging growth quality across provinces and for the whole country, therefore a worthwhile effort to pursue.

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Declaration of competing interest

None.

Appendix 1. Sensitivity analysis

In the main text, we estimate ML index using volumes of industrial waste gas, waste water and solid wastes as undesirable outputs, based on DDF with direction vector (y, -b). We perform four sensitivity analysis here to check the robustness of ML indexes to the model choice and to the undesirable output choice. Correlations between the ML results under alternative settings and the baseline results are separately scattered in Fig. S1. In general, the results are robust to various changes.

First, we change the distance function to Shephard distance function (Shephard, 1970), which is equivalent to direction of (y, b) in DDF. In this setting, good outputs and bad outputs have to change proportionately, which means the only way to reduce undesirable output is to reduce production. The distance function can be computed by solving the following linear programming problems. As an example, for k:

$$\overrightarrow{D}_s^{t,k}(x^{t,k}, y^{t,k}, b^{t,k}; y^{t,k}, -b^{t,k}) = \max\theta \tag{S1}$$

$$s.\ t.\ \sum_{k=1}^{K} z_k y_{k,m}^t \geq \theta y_{k,m}^t,\ m = 1,\ \dots, M$$

$$\sum_{k=1}^{K} z_k b_{k,l}^t = \theta b_{k,l}^t,\ l = 1,\ \dots, L$$

$$\sum_{k=1}^{K} z_k x_{k,n}^t \leq x_{k,n}^t,\ n = 1,\ \dots, N$$

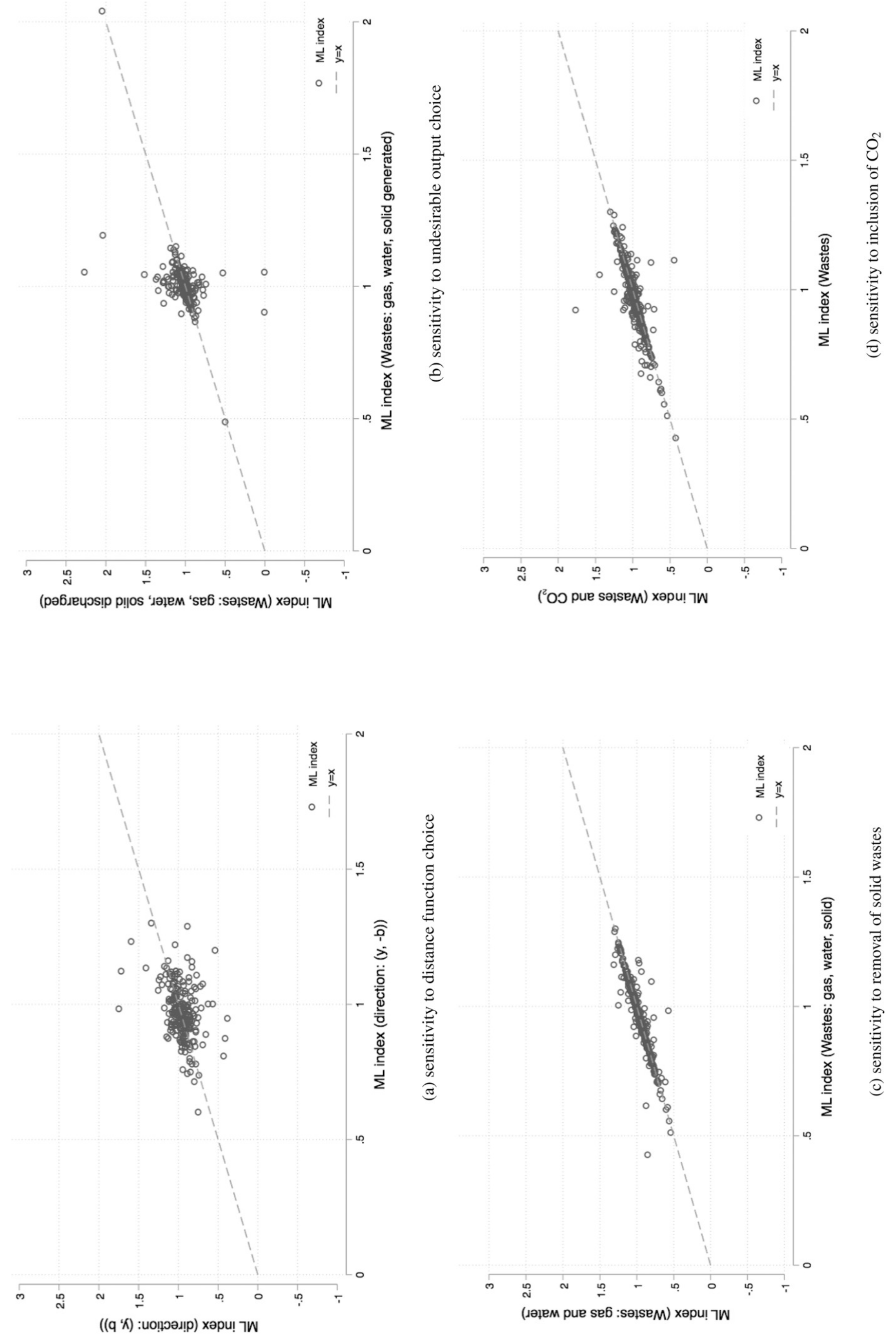
$$z_k \geq 0,\ k = 1,\ \dots, K$$

Based on Fig. S1(a), there are differences between the ML index results calculated using different direction vectors, but points scatter around the line where two ML index are equal.

Second, we replace the indicator of industrial solid wastes produced with the industrial solid wastes discharged, which is another statistic reported in the Statistical Yearbook, referring to the amount of solid waste emitted outside the solid waste treatment facilities and sites. Volumes of industrial solid wastes discharged are much smaller, and close to zero for many provinces especially in recent years, as they are the wastes directly discharged to the environment illegally. In Fig. S1(b), except a few outliers, most points locate around the value of unity in terms of both x axis and y axis. Variances of ML index are larger when using the indicator of industrial solid wastes discharged.

Third, we remove the industrial solid wastes from undesirable outputs, i.e., include only industrial waste water and gas as bad outputs. The results are robust as there is strong correlation between these two sets of results in Fig. S1(c).

Fourth, we add CO_2 emission as the undesirable output to include broader environmental damages and take account of energy use. The results are consistent with the baseline indicated by Fig. S1(d).



(a) sensitivity to distance function choice

(b) sensitivity to undesirable output choice

(c) sensitivity to removal of solid wastes

(d) sensitivity to inclusion of CO_2

Fig. S1. Correlation of ML indexes subject to various model changes.

Appendix 2. GTFP in the secondary industry

We explore the effects of industrial structure on the GTFP growth in the main text, and green productivity changes within the secondary sector (largely manufacturing), ruling out agriculture and service sector, would be interesting to discuss and might help provide more insights on the growth patterns across the Chinese provinces.

We combine data of labor, capital, and GDP at 1978 prices, restricted to the secondary industry only, also from national and provincial statistical yearbooks, with the undesirable outputs of industrial wastes, during 1997–2015. Following the same procedure, Malmquist index and ML index are computed using DDF approach, measuring TFP and GTFP changes within the secondary industry sector. We reproduce some main figures analog to those in the main text, which depict the GDP, TFP and GTFP growing patterns over time and across provinces.

Trends of GDP, TFP and GTFP growth of the industry sector (Fig. S2 are quite different from those for the whole economy in Fig. 2. Growth rates for the three indicators exhibit alike trends until 2010. The average growth rates of secondary industry GDP are much lower than the total GDP, and there is no obvious decline trend in TFP growth or GTFP growth. TFP growth peaks in 2011 and then goes down to negative growth thereafter, while GTFP growth bottoms in 2011 to 2012 and then rebound.

Next, we compare the mean growth rates across provinces. Rankings of provinces according to their secondary-industry GDPr, Mb, and MLb respectively are presented in Fig. S3. Ningxia, Xinjiang, Guizhou, Shaanxi, and Qinghai are the top 5 with fastest growth in the secondary industry sector. The mean growth rate in secondary industry GDP over 1998–2015 for Beijing is less than 1\%, and for shanghai is negative.

Still, under the TFP measure for the secondary industry, results are totally different. Zhejiang overwhelms all the other provinces, being the only one with dramatic productivity improvement in the secondary industry sector. Beijing ranked 4th who ranked middle GDP growth of secondary industry. Malmquist index for the industry sector in Shanghai keeps around unity, meaning despite the secondary industry shrinks, the productivity remains.

Including the assessment of environmental impact of the secondary industry growth, rankings among provinces changed again. Beijing, Liaoning and Shanghai, stood out with ML indexes greater than unity, i.e., their green productivity efficiency improved even within the secondary industry sector. Guangdong and Jiangsu perform worst in the green productivity of industry sector.

Maps of GDP growth, TFP growth and GTFP growth within the secondary industry are shown in Fig. S4(a–c), where darker colors represent larger growth rates. Fig. S4(d) displays the changes from GDP growth ranking to GTFP growth ranking, and Fig. S4(e) displays the changes from TFP growth ranking to GTFP growth ranking, with blue for higher position and red for lower position. Different from the spatial distribution of aggregated GTFP growth of the whole economy revealed by Fig. 4, south-eastern regions are doing badly in the productivity of secondary industry sector after incorporating environmental performances. However, as we suggest in Section 3 in the main text, using total discharge of industrial wastes as undesirable outputs might bias down GTFP measures in southeastern China, as they normally implement stricter emission standards, and they might have higher data quality while others might under report pollution.

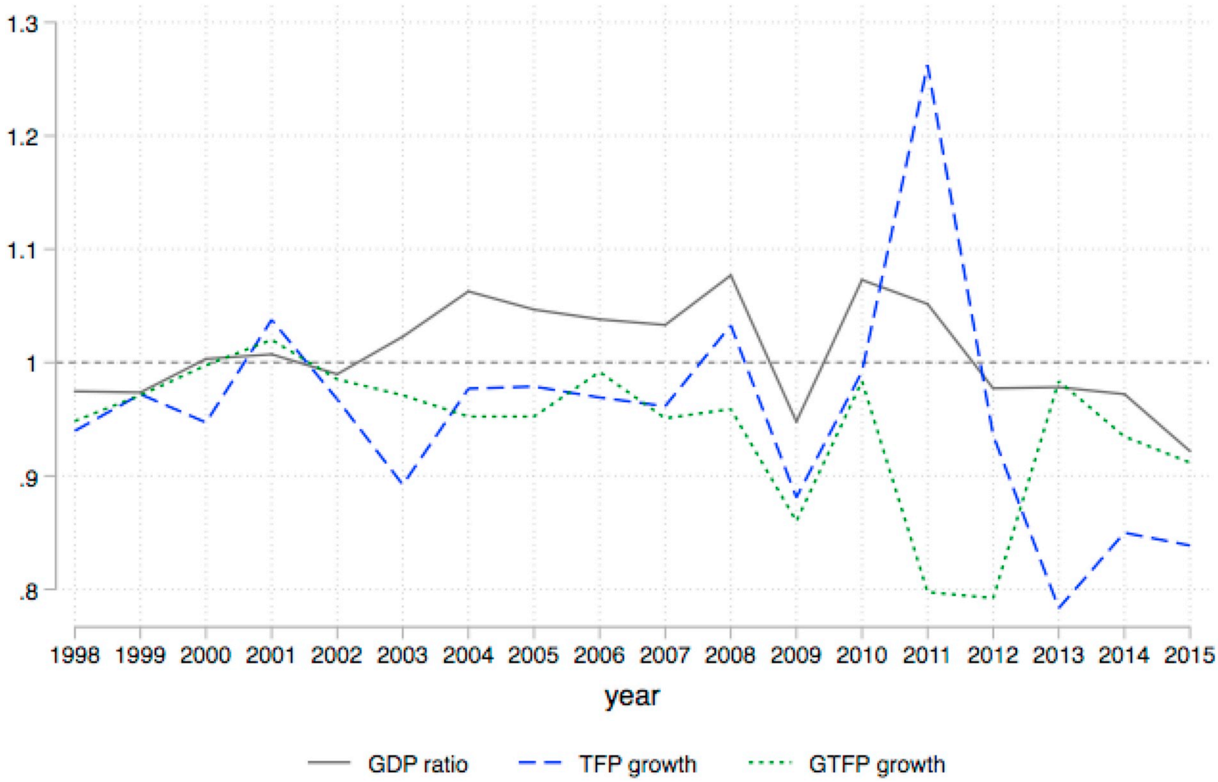


Fig. S2. Time trends of national aggregated GDP, TFP and GTFP growth of industry sector, 1998–2015.

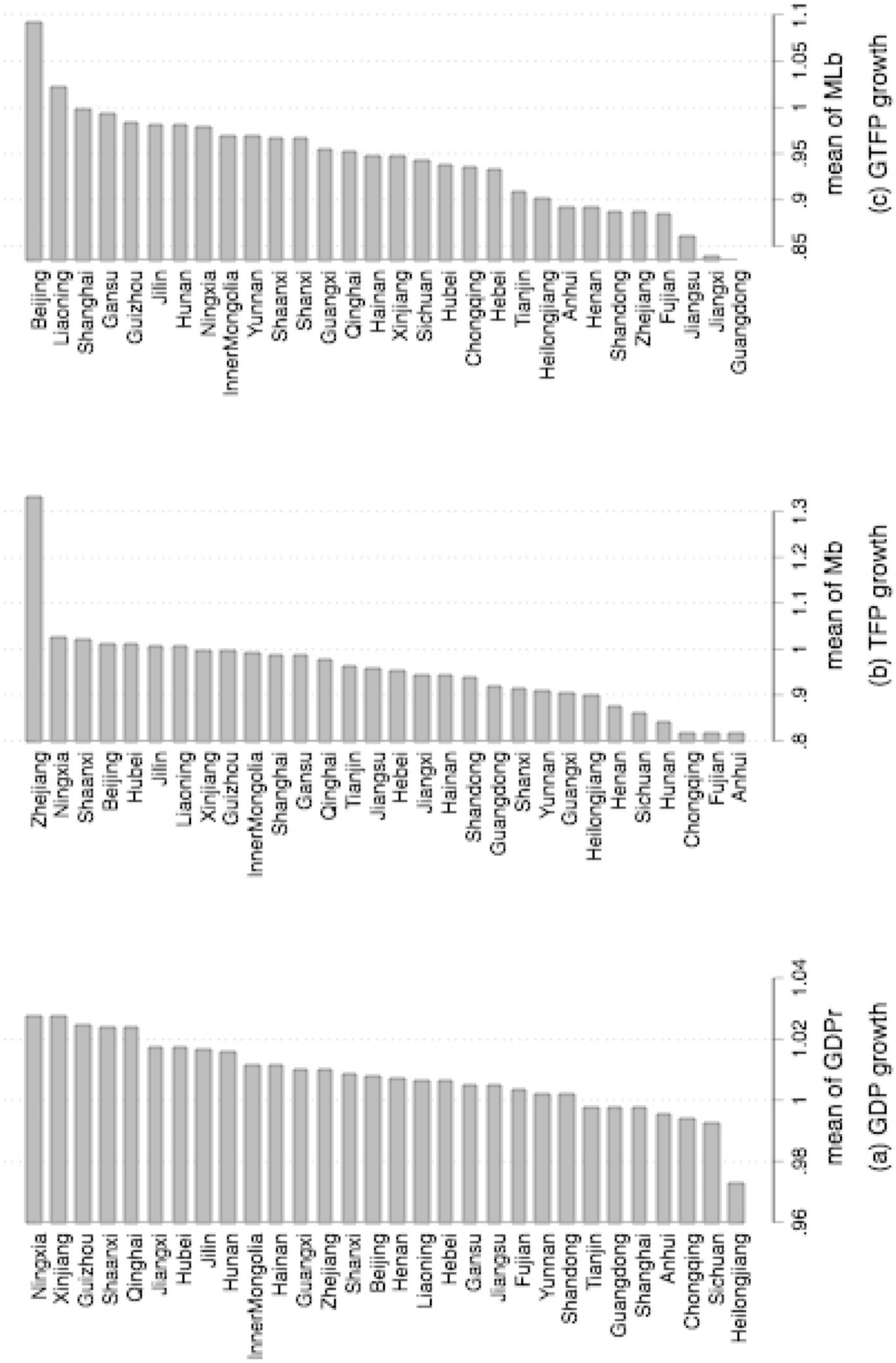


Fig. S3. Rankings of provinces by average GDP, TFP and GTFP growth of industry sector over 1998–2015.

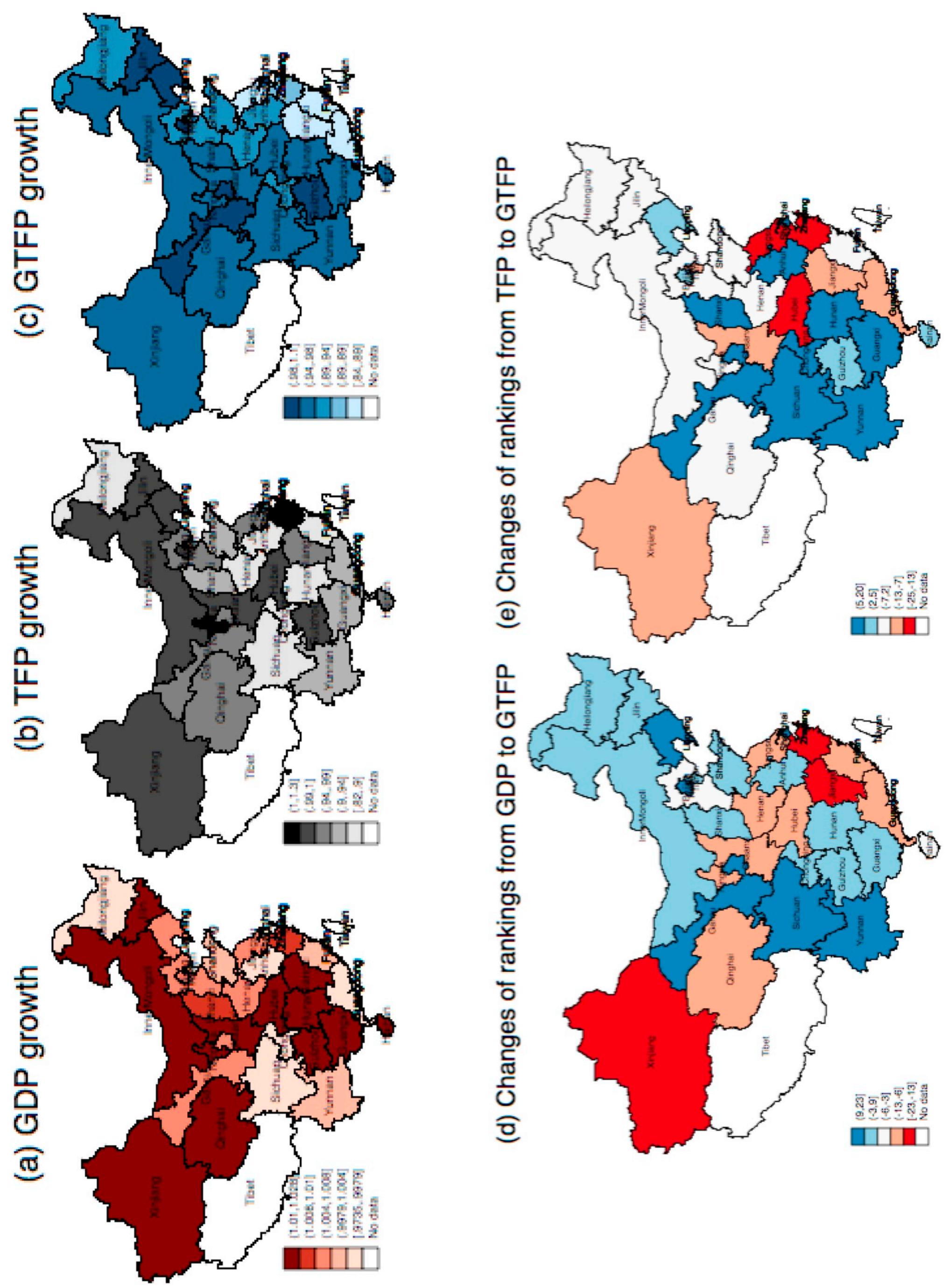


Fig. S4. Divergence in spatial distribution of GDP, TFP and GTFP growth of industry sector over 1998–2015.
Notes: Blue stands for the rise of ranking based on GTFP growth relative to that based on GDP growth, and red stands for the decline.

Appendix 3. Time trends of GDP, TFP, GTFP growth by province

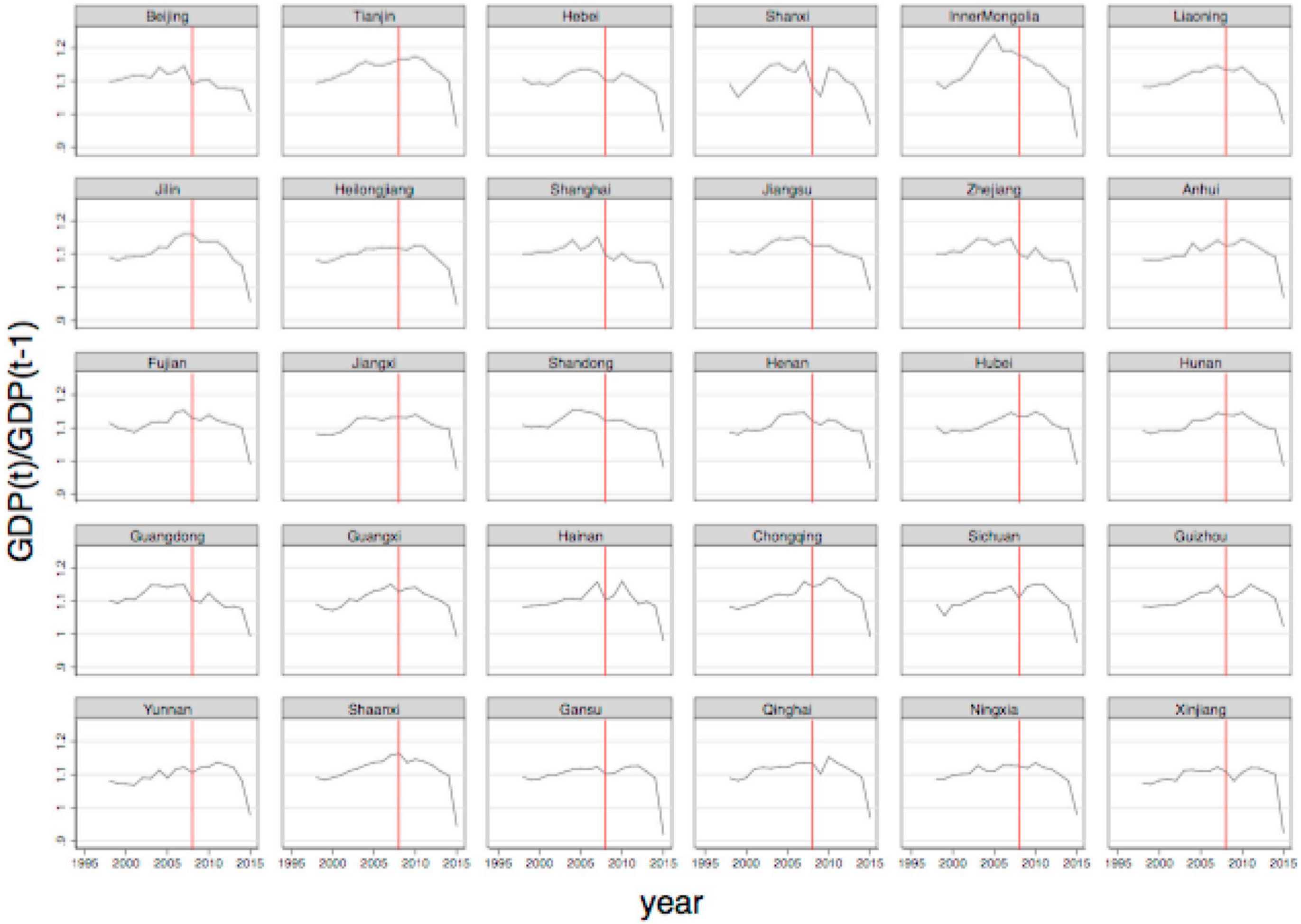


Fig. S5. Trend of GDP growth by province.
Notes: Red line is year 2008. Reverse U-shape. GDP growth has slowed down since 2008.

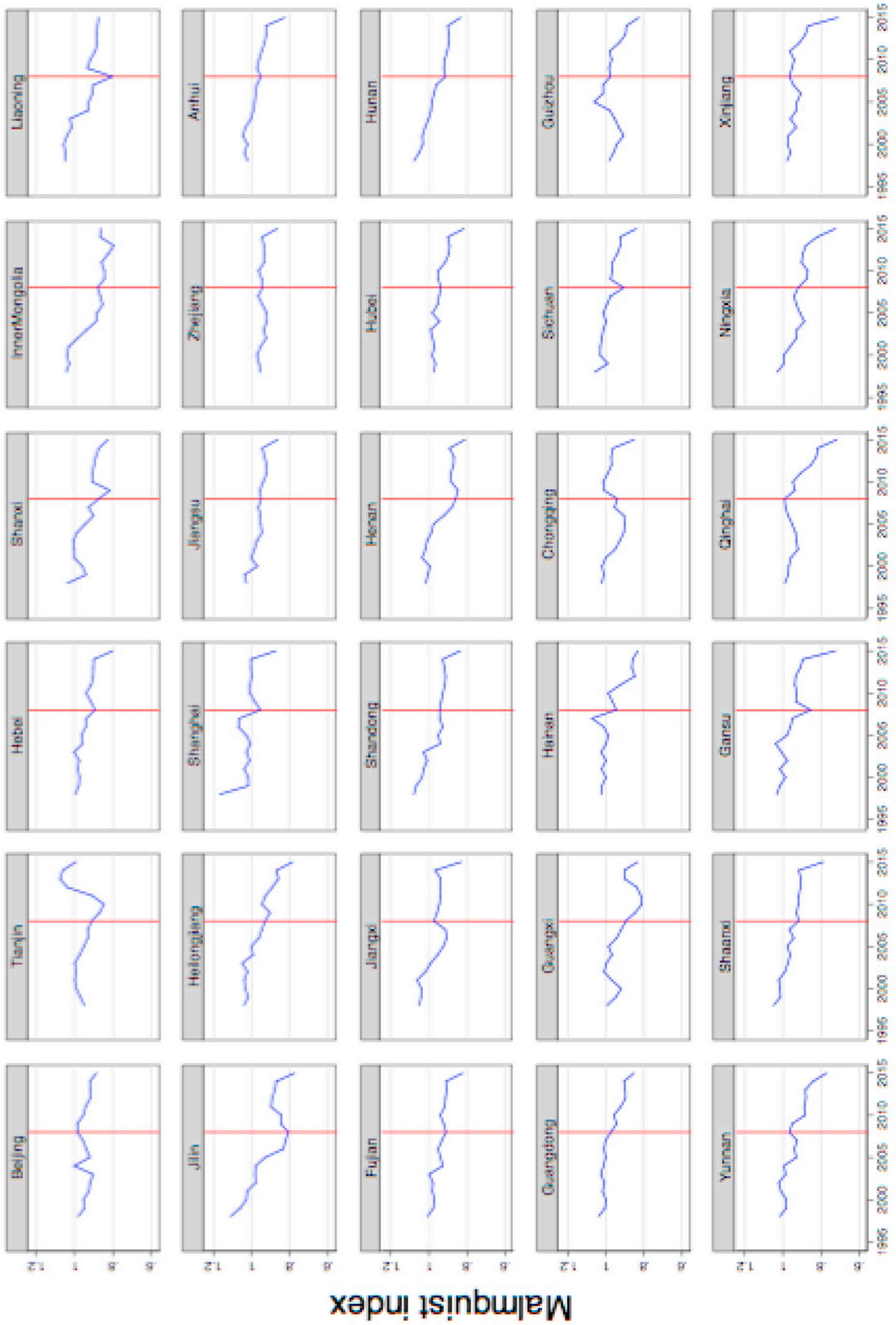


Fig. S6. Trend of TFP growth by province.
Notes: Continuous downward trends for most provinces.

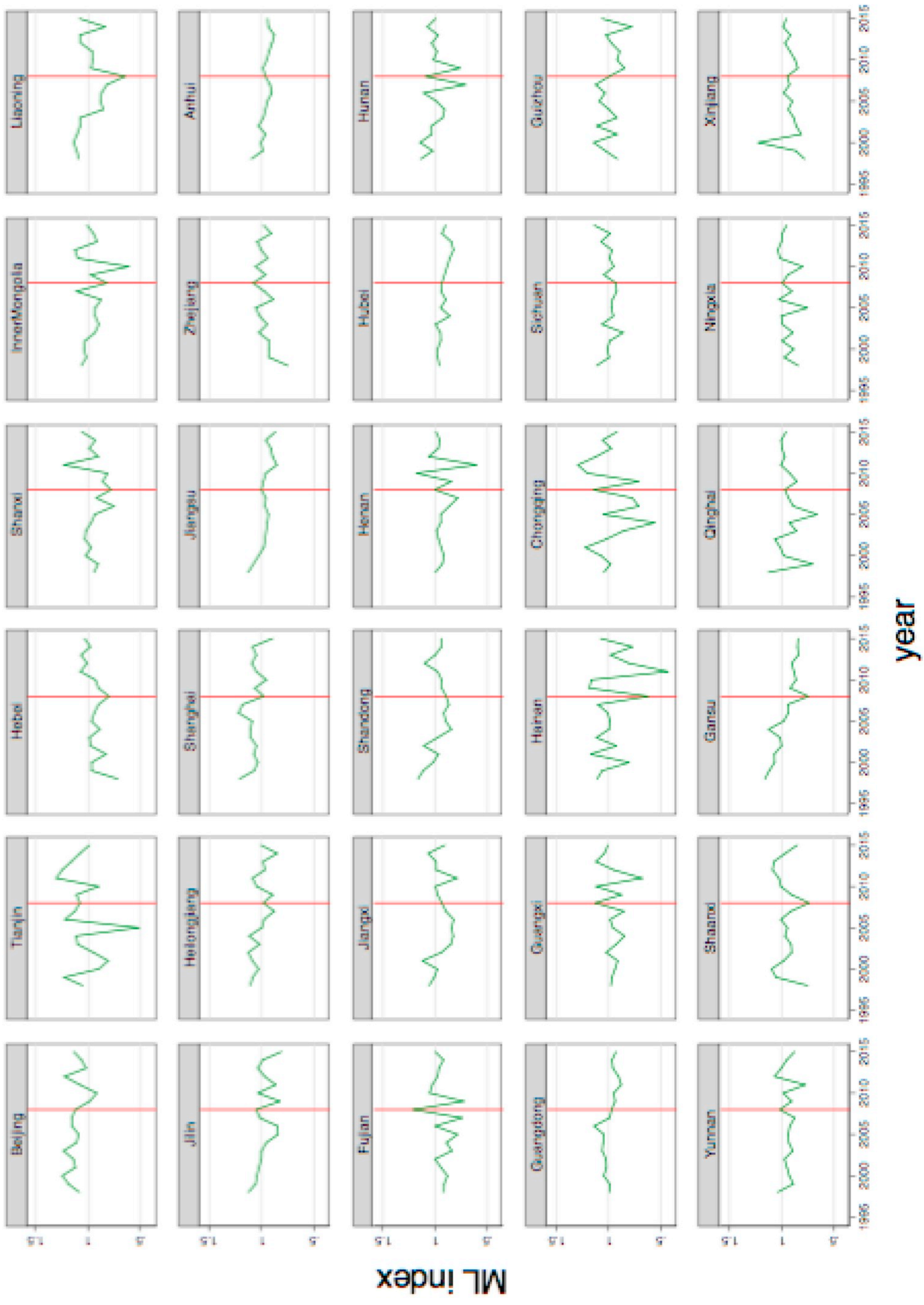


Fig. S5. Trend of GTFP growth by province.
Notes: No obvious upward or downward trends. Relative flat or fluctuate around certain level for most provinces.

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