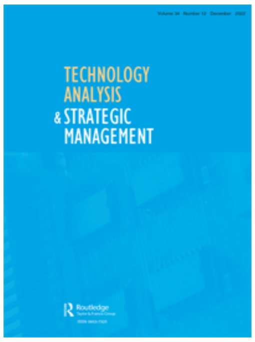

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Efficiency measurement and productivity progress of regional green technology innovation in China: a comprehensive analytical framework

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ABSTRACT

An effective innovation is a significant cause of competitive advantage. The evaluation of regional green technology innovation (GTI) performance in China has gained tremendous interest. In this paper, the GTI activities are split into two components: the green technology R&D (GTR) stage and the technology achievement transformation (TAT) stage. While doing so, we consider the time lag of the GTI process and managerial disposability of the undesirable output. The combination of the network epsilon-based measure (EBM) model and meta-frontier Malmquist-Luenberger (MML) index constitutes a comprehensive analytical framework for evaluating the regional GTI performance in China. This study's empirical results indicate that: (1) China's overall average efficiency of GTI (0.817) is between the efficiency of GTR (0.725) and the efficiency of TAT (0.929); (2) the average efficiencies in the GTR stage fluctuate considerably, with average efficiencies relatively high and constant in the TAT stage; (3) technological progress is the key element which contributes to improvements in the MML index of overall and sub-process GTI; and (4) from a national perspective, the MML index of the overall GTI varies from 0.980 to 1.128 each year, with an average annual growth of 2.8%.

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Green technology innovation; network EBM model; meta-frontier Malmquist-Luenberger index; data envelopment analysis

1. Introduction

China has entered into a new normal economic development, and at this stage, effectively maximising the distribution of innovation resources and enhancing innovation efficiency are key issues facing China's implementation of innovation-driven strategy. The effective way to overcome resource and environmental constraints is through green technology innovation (GTI) (Du, Liu, and Diao 2019). GTI takes into account the problems of resources and ecological environment, which is a distinctive feature different from traditional technological innovation (Wang, Xie, and Yang 2017). Therefore, it is still of considerable theoretical and practical importance to enrich the tools to evaluate innovation efficiency and to examine the key driving factors influencing innovation efficiency.

Initially introduced by Charnes, Cooper, and Rhodes (1978), data envelopment analysis (DEA) is a nonparametric linear programming technique, which can be used to analyse the relative efficiency of decision making units (DMUs) with multiple outputs and inputs. As a common data-driven tool, DEA

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has been adopted by a variety of scholars to analyse efficiency in different fields (Emrouznejad and Yang 2018), especially in evaluating innovation performance. Each DMU is known as a 'black box' in traditional DEA models, in which the intermediary phases between inputs and outputs are ignored. As for the network structure, Cook, Liang, and Zhu (2010) reviewed two-stage network models and discussed future perspectives and challenges.

Related research on measurement-oriented technology innovation activities are burgeoning in the literature. However, different network DEA models may only apply to specific situations. Thus, how to construct a network DEA model to simulate the GTI process effectively is an important issue. Another concern is that previous researchers mainly focused on technology innovation efficiency, neglecting 'green' factors (Wu, Wang, and Qian 2020). Thus, how to integrate undesirable outputs into the GTI process properly is a second important issue. Besides, at the regional level, the subgroups of China exist in various group-specific production technologies, which could not be comparable, due to unbalanced regional growth (Li et al. 2017). Thus, a third important issue is how to investigate the main driving factors and regional technology gap synthetically.

We establish a two-stage network epsilon-based measure (NEBM) model that includes initial inputs, free intermediate outputs, additional intermediate inputs, desirable outputs, and undesirable outputs. To account for regional heterogeneity and the time lag of the network structure, the meta-frontier Malmquist-Luenberger (MML) index is used to empirically study the main driving factors and regional technology gap of GTI activities in China. The research contributions are mainly embodied in the following four aspects.

First, we provide an evaluation framework incorporating a complicated internal structure and undesirable outputs to study the GTI efficiency of regions in China during the '12th Five-Year Plan (2011–2015)' period. Second, we empirically assessed and decomposed the GTI efficiency using the NEBM model with managerial disposability. Third, we compared various network DEA models, such as the traditional two-stage DEA, network CCR (NCCR), network slack-based measure (NSBM), and NEBM model. Fourth, the productivity change and technical gap ratio was evaluated by MML index, considering the regional heterogeneity and time lag.

The remainder of this paper is structured as follows. In Section 2, we review the relevant literature. Methodology is provided in Section 3, and we describe the network structure, data, and variables in Section 4. In Section 5, we present the empirical results and discussions. Finally, we conclude this paper in Section 6.

2. Literature review

2.1. Research on network DEA and the MML index

Two-stage DEA modelling helps to determine DMU's overall efficiency and corresponding stage efficiencies. Thus, specific internal information stored in the network structure may also be identified. After the formation of multiplicative model with the two-stage (Kao and Hwang 2008), a multi-period two-stage DEA model was proposed to consider the operations of individual periods (Kao and Hwang 2014). In addition, Chen et al. (2009) established a two-stage additive DEA method. Then, Cook et al. (2010) introduced a general network structure based on the two-stage additive modelling.

However, radial models, considering proportional changes, deviate from most practical operations and disregard input or output slacks. As non-proportional changes could exist in inputs and outputs, Tone and Tsutsui (2009) suggested a network SBM technique with slack variables to measure efficiency. For a two-stage method that recognises undesirable outputs, Fukuyama and Weber (2010) suggested a slack-based inefficiency measure. However, these models are not suitable where problems require simultaneous analysis of the radial and non-radial inputs and outputs. The network EBM model was proposed by Tavana et al. (2013) to integrate radial and non-radial approaches into a single system. However, the NEBM model does not take the indicator of undesirable outputs into account. Then, Cui and Li (2018) introduced the NEBM model with managerial disposability.

Many researchers have investigated innovation efficiency and analysed the growth rate in China, but the heterogeneity of DMUs does not take into account and assumes that the same production frontier are suitable for all DMUs. A main analytical paradigm has been developed by O'Donnell, Rao, and Battese (2008), where the meta-frontier can be calculated by nonparametric and parametric approaches. Oh and Lee (2010) introduced the meta-frontier Malmquist approach, which can incorporate the technology heterogeneity and depict the technology gap. On this basis, Oh (2010) proposed the MML index, which handles undesirable environmental factors.

2.2. Research on Green technology innovation

The evaluation of innovation activities attracts significant interest from researchers, and owing to its benefits, DEA has been widely adopted (Xiong, Yang, and Guan 2018). A two-stage dynamic network DEA approach incorporating shared outputs was proposed by An et al. (2020) to evaluate the performance of high-tech industries. Chen, Liu, and Zhu (2018) introduced a conceptual model to estimate the GTI for high-tech industries. Zhang, Luo, and Chiu (2019) employed the Russell multi-activity network DEA model to appraise the innovation performance of high-tech industries. Using a two-stage DEA approach, Liu et al. (2019) investigated R&D performance of industrial enterprises.

However, prior research efforts have mainly focused on technology innovation efficiency and neglected the 'green' factors. There are various approaches based on different criteria for the handling of undesirable outputs. In specific, managerial disposability means that the DMU increases input consumption in order to maximise desirable outputs and at the same time minimise unnecessary outputs. In evaluating DMU adaptive behaviours to adjustments in the environmental regulations, the managerial disposability must be taken into account.

As for the evaluation of GTI efficiency, scholars conducted a great deal of research based on different modelling tools. Du, Cheng, and Yao (2021) explored the heterogeneous impacts of environmental regulation on GTI and industrial structure. In strategic emerging industries, Sun, Miao, and Yang (2017) explored the ecological-economic performance of GTI. A stochastic frontier analysis was carried out by Miao et al. (2017) to study GTI's effect on the usage of natural resources.

In addition, many scholars use DEA models to investigate GTI efficiency. Wang et al. (2017) studied the unified green innovation performance by using DEA-RAM model. Lin et al. (2018) adopted DEA window analysis approach to measure the GTI efficiency. Luo et al. (2019) investigated strategic emerging industries' GTI efficiency by using the Malmquist-DEA index.

2.3. Summary of the literature review

In view of the network production structure existing in real life, we are required to determine a reasonable evaluation method according to the situation of specific problems. Although the network DEA approach is commonly adopted in the evaluation of GTI, no studies consider the network EBM model with managerial disposability to deal with the undesirable outputs. Therefore, it is of great significance to combine the network DEA model with managerial disposability for the assessment of regional GTI in China.

Also, no studies introduce regional heterogeneity into the network structure. Regional advantages, resource endowments and institutional systems of different regions in China are different. It is easy to form regional technical barriers, which affect the speed of technology diffusion, and make the GTI sets of different regions have differences, that is, the frontier of production technology has differences. Therefore, if different production frontiers are used in different regions, there will be a lack of common reference standards between regions.

3. Methodology

3.1. Network EBM model

A unifying model for integrating radial as well as nonradial features was proposed by Tone and Tsutsui (2010). The non-oriented EBM model is constructed as follows, given the constant returns to scale.

$$\rho^* = \min \frac{\theta - \varepsilon_x \sum_{i=1}^{m} \frac{w_i^- s_i^-}{x_{i0}}}{\eta + \varepsilon_y \sum_{r=1}^{s} \frac{w_r^+ s_r^+}{y_{r0}}}$$

$$s.t. \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{i0}, i = 1, 2, \ldots, m \tag{1}$$

$$\sum_{j=1}^{n} \lambda_j y_{ry} - s_r^+ = \eta y_{r0}, r = 1, 2, \ldots, s$$

$$\lambda \geq 0, s^- \geq 0, s^+ \geq 0$$

In this model, x_{ij} and y_{rj} represent the i-th input and the r-th output of DMU_j, respectively. The number of DMUs, outputs, and inputs are represented by n, s and m, respectively, and s_i^- and s_r^+ are the slacks of the i-th input and the r-th output. The parameters λ_j are the intensity variables. Parameters w_i^- and w_r^+ model the relative importance of input i and output r, and satisfy $\sum_{i=1}^{m} w_i^- = 1$ and $\sum_{r=1}^{s} w_r^+ = 1$, with $w_i^- \geq 0$ and $w_r^+ \geq 0$. The higher the affinity degree between inputs and outputs is, the more weight is allocated. Parameters ε_x and ε_y can integrate the radial and nonradial slack models, and should be given in advance. The equality $\varepsilon_x = \varepsilon_y = 0$ implies that the EBM model is a CCR model, while $\varepsilon_x = \varepsilon_y = 1$ implies that the EBM model is an SBM model.

The traditional EBM model makes no claims as to the internal functioning of the DMU (Deng and Yan 2019). While in network DEA, the performance of each stage can be evaluated by specifying all stages in sub-DMUs. Figure 1 illustrates the structure of two-stage network model.

On the basis of the traditional two-stage network SBM model, Tavana et al. (2013) proposed the network EBM model, which took into account both the proportion improvement of CCR model and the slack improvement of SBM model. The network EBM model proposed by Tavana et al. (2013) is constructed as follows.

$$\tau^* = \min \frac{\sum_{h=1}^{H} W_h \left(\theta^h - \varepsilon_x^h \sum_{i=1}^{m_h} \frac{w_i^{h-} s_i^{h-}}{x_{i0}^h} \right)}{\sum_{h=1}^{H} W_h \left(\eta^h + \varepsilon_y^h \sum_{r=1}^{s_h} \frac{w_r^{h+} s_r^{h+}}{y_{r0}^h} \right)}$$

$$s.t. \sum_{j=1}^{n} \lambda_j^h x_{ij}^h + s_i^{h-} = \theta^h x_{i0}^h, i = 1, 2, \ldots, m_h$$

$$\sum_{j=1}^{n} \lambda_j^h y_{rj}^h - s_r^{h+} = \eta^h y_{r0}^h, r = 1, 2, \ldots, s_h \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j^k z_{tj}^{(k,h)} = \sum_{j=1}^{n} \lambda_j^h z_{tj}^{(k,h)}, t = 1, 2, \ldots, l_h$$

$$h, k = 1, 2, \ldots, H, \lambda_j^h \geq 0, s^{h-} \geq 0, s^{h+} \geq 0$$

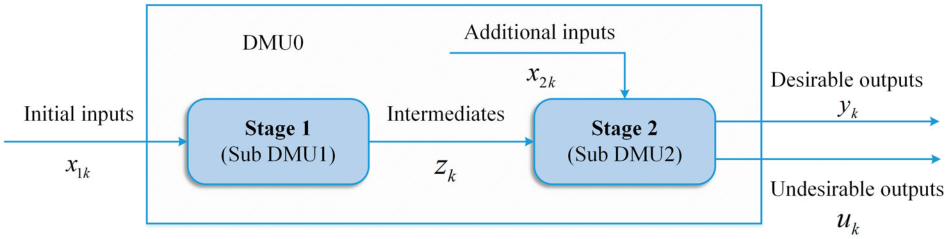

Figure 1. Two-stage network structure.

In this model, H is the number of the divisions and x_{ij}^h and y_{rj}^h represents the i-th input and r-th output of DMU_j of division h, respectively, while m_h and s_h denote the number of the inputs and outputs of division h, respectively. The parameter $z^{(k,h)}$ denotes the intermediate measures between division k and division h, and l_h stands for the number of the intermediate measures of division h. Parameter W_h denotes the weight of division h. The relative importance of input i and output r in division h are denoted by w_i^{h-} and w_r^{h+}, which satisfy $\sum_{i=1}^{m_h} w_i^{h-} = 1$ and $\sum_{r=1}^{s_h} w_r^{h+} = 1$, $w_i^{h-} \geq 0$ and $w_r^{h+} \geq 0$. Finally, ε_x^h and ε_y^h are the parameters of division h that can integrate the radial and non-radial slack models.

According to the study of Cui and Li (2018), the network EBM model with managerial disposability is constructed as follows.

$$\gamma^* = \min \frac{\sum_{h=1}^{H} W_h\left(\theta^h - \varepsilon_u^h \sum_{p=1}^{p_h} \frac{w_p^{h-} s_p^{h-}}{u_{p0}^h}\right)}{\sum_{h=1}^{H} W_h\left(\eta^h + \varepsilon_{x,y}^h w_{x,y}^{h+}\left(\sum_{r=1}^{s_h} \frac{s_r^{h+}}{y_{r0}^h} + \sum_{i=1}^{m_h} \frac{s_i^{h+}}{x_{i0}^h}\right)\right)}$$

$$\begin{aligned}
s.t. &\sum_{j=1}^{n} \lambda_j^h x_{ij}^h - s_i^{h+} = \eta^h x_{i0}^h,\ i = 1, 2, \ldots, m_h \\
&\sum_{j=1}^{n} \lambda_j^h y_{rj}^h - s_r^{h+} = \eta^h y_{r0}^h,\ r = 1, 2, \ldots, s_h \\
&\sum_{j=1}^{n} \lambda_j^h u_{pj}^h + s_p^{uh-} = \theta^h u_{p0}^h,\ p = 1, 2, \ldots, p_h \\
&\sum_{j=1}^{n} \lambda_j^k z_{tj}^{(k,h)} = \sum_{j=1}^{n} \lambda_j^h z_{tj}^{(k,h)},\ t = 1, 2, \ldots, l_h \\
&h, k = 1, 2, \ldots, H,\ \lambda_j^h \geq 0,\ s^{h-} \geq 0,\ s^{h+} \geq 0
\end{aligned} \tag{3}$$

In this model, H is the number of the divisions. The parameters x_{ij}^h, y_{rj}^h and u_{pj}^h represent the i-th input, r-th desirable output, and the p-th undesirable output of DMU_j of division h, respectively. The parameters m_h, s_h and p_h denote the number of the inputs, desirable outputs, and the undesirable outputs of division h, respectively. Parameter $z^{(k,h)}$ denotes the intermediate measures between division k and division h. Parameter W_h stands for the weight of division h and is determined by the decision-maker. The parameter w_p^{h-} is the importance degree of undesirable output p, while parameter $w_{x,y}^{h+}$ is the importance degree of the input and desirable output in division h. They satisfy $\sum_{i=1}^{p_h} w_p^{h-} = 1$ and $\sum_{i=1}^{m_h+s_h} w_{x,y}^{h+} = 1$, $w_p^{h-} \geq 0$ and $w_{x,y}^{h+} \geq 0$. Based on the dispersion degree, parameters ε_u^h and $\varepsilon_{x,y}^h$ are determined, and they allow this model to combine the radial and nonradial slack models. Cui and Li (2018) also provided the steps to determine ε_u^h, $\varepsilon_{x,y}^h$, w_p^{h-}, and $w_{x,y}^{h+}$.

By changing it into a linear programme, Model (3) can be solved with the transformation of Charnes and Cooper (1962). The undesirable outputs are parts of stage 2 instead of stage 1. Thus, for the NEBM model, the efficiency is determined as follows for each division.

$$\gamma^{h1*} = \frac{\theta^h - \varepsilon_x^h \sum_{i=1}^{m_h} \frac{w_i^{h-} s_i^{h-*}}{x_{i0}^h}}{\eta^h + \varepsilon_y^h \sum_{r=1}^{s_h} \frac{w_r^{h+} s_r^{h+*}}{y_{r0}^h}} \tag{4}$$

$$\gamma^{h2*} = \frac{\theta^h - \varepsilon_u^h \sum_{p=1}^{p_h} \frac{w_p^{h-} s_p^{h-*}}{u_{p0}^h}}{\eta^h + \varepsilon_{x,y}^h w_{x,y}^{h+} \left(\sum_{r=1}^{s_h} \frac{s_r^{h+*}}{y_{r0}^h} + \sum_{i=1}^{m_h} \frac{s_r^{h+*}}{y_{r0}^h} \right)} \tag{5}$$

3.2. Meta-frontier Malmquist-Luenberger index

All DMUs are classified into K groups, and feasible input-output combinations of DMUs in each group G_k belong to the same technology set. Oh (2010) developed the MML index and divided the benchmark technology set (BTS) as follows.

1. The contemporaneous BTS of group G_k in period t is defined as $P_{G_k}^{C^t} = \{(x^t, y^t, u^t) | x^t canproduce(y^t, u^t)\}$, $t = 1, \ldots, T$. This set contains all the observations of group G_k only in period t. It represents a production technology consisting of production frontiers containing all DMUs of the group at the same time.
2. The inter-temporal BTS of group G_k is defined as $P_{G_k}^I = P_{G_k}^{c^1} \cup P_{G_k}^{c^2} \ldots \cup P_{G_k}^{c^T}$. This set includes all observations of group G_k in all the periods. It denotes that DMUs of the group in different periods are put together to construct production frontiers, and then the technical efficiency of each DMU in each period is calculated according to this production frontiers.
3. The global BTS is defined as $P^G = P_{G_1}^I \cup P_{G_2}^I \ldots \cup P_{G_k}^I$. This set includes all observations of all groups in all the periods. It represents all periods of all DMUs as reference production frontiers, and then calculates the technical efficiency in different periods of each region.

According to the study of Oh (2010), the MML index can be decomposed into the EC index, the best practice gap change (BPC) index, and the technical gap ratio change ($TGRC$) index with the following equation.

$$\begin{aligned} MML_{t+1}^t(x^t, y^t, u^t, x^{t+1}, y^{t+1}, u^{t+1}) &= \frac{1 + D^G(x^t, y^t, u^t)}{1 + D^G(x^{t+1}, y^{t+1}, u^{t+1})} \\ &= \frac{1 + D^{C^t}(x^t, y^t, u^t)}{1 + D^{C^{t+1}}(x^{t+1}, y^{t+1}, u^{t+1})} \times \frac{(1 + D^I(x^t, y^t, u^t))/(1 + D^{C^t}(x^t, y^t, u^t))}{(1 + D^I(x^{t+1}, y^{t+1}, u^{t+1}))/(1 + D^{C^{t+1}}(x^t, y^t, u^t))} \\ &\times \frac{(1 + D^G(x^t, y^t, u^t))/(1 + D^I(x^t, y^t, u^t))}{(1 + D^G(x^{t+1}, y^{t+1}, u^{t+1}))/(1 + D^I(x^t, y^t, u^t))} \\ &= \frac{TE^{t+1}}{TE^t} \times \frac{BPR^{t+1}}{BPR^t} \times \frac{TGR^{t+1}}{TGR^t} = EC_{t+1}^t \times BPC_{t+1}^t \times TGC_{t+1}^t \end{aligned} \tag{6}$$

In the above equation, TE^t represents technical efficiency in period t, and BPR^t represents the best practice gap ratio between best practice frontier and inter-temporal best practice frontier. TGR^t represents the technical gap ratio in period t, meaning the gap between inter-temporal technology and global technology. If $TGR^t = 1$, then the DMU is on the meta-frontier for innovation technology in period t. The explanations of EC, BPC, and TGC are given in detail as follows.

1. *EC* represents the technical efficiency change during two periods, reflecting relative change rate when DMUs move to the contemporaneous benchmark technology frontier during period t to $t+1$.
2. *BPC* represents the change of the best practice gap ratio during two periods, reflecting technical change.
3. *TGC* is the change of technical gap ratio between inter-temporal and global benchmark technology frontier in the two periods. *TGC* reflects the technical catch-up effect of DMUs.

4. Data and variables

4.1. Network structure

This paper evaluates the GTI efficiency of 30 provinces (we use 'province' to cover autonomous regions and municipalities also) based on panel data from 2011 to 2017. Due to the lack of details, this work does not include Tibet, Taiwan, Hong Kong and Macao. Figure 2 illustrates the indicator system. Table 1 describes the indicators in detail and its corresponding notations. Data are collected from China Science and Technology Statistical Yearbook, China Statistical Yearbook, China Energy Statistical Yearbook and China Environment Statistical Yearbook.

4.2. Data processing

To represent R&D capital stock, the consumer price index (*CPI*) and producer price index (*PPI*) of each province are adopted to generate the R&D price index. Also, when analysing two-stage network operations, time lags are critical to be addressed. Reflecting the two-stage phase of GTI, this study follows Chen, Liu, and Zhu (2018) and Wang et al. (2020) in considering a two-year lag for the GTI process.

The flow data of R&D expenditure in the GTI activities can be supplemented by the stock data, which is estimated by the perpetual inventory method. Formula (7) is used to estimate R&D capital stock. For the calculation of the base period R&D capital stock, the Formula (8) is adopted.

$$K_t = (1-\delta)K_{t-1} + E_{t-1} \tag{7}$$

$$K_0 = \frac{E_0}{(g+\delta)} \tag{8}$$

It should be noted that the expenditure for technical transformation is a comprehensive indicator. To clarify the index structure, the entropy method is used to integrate the dedicated inputs into one indicator. In consideration of the fact that no official statistics on each province's CO_2 emissions have

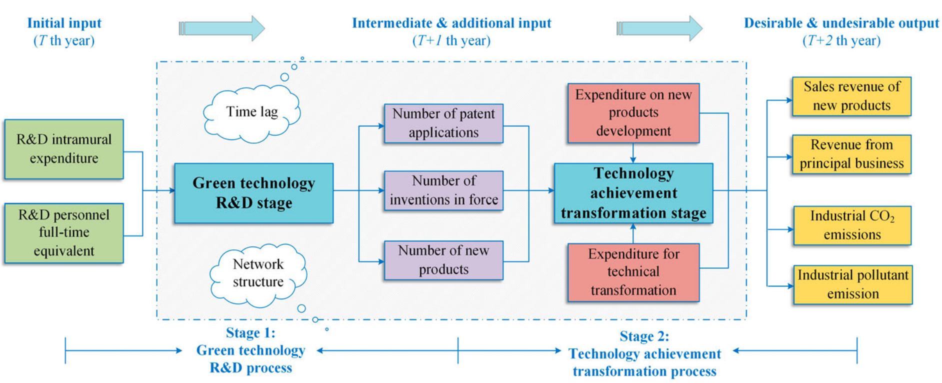

Figure 2. A two-stage production structure of the green technology innovation process.

Table 1. Description of indicators used in this paper.

Indicator	Type	Unit	Notation
R&D intramural expenditure	Initial input	10 thousand CNY	*Exp.*
R&D personnel full-time equivalent		Person	*Per.*
Number of patent applications	Intermediate	Piece	*Pat.*
Number of inventions in force		Piece	*Inv.*
Number of new products		Item	*Pro.*
Expenditure on new products development	Additional input	10 thousand CNY	*Dev.*
Expenditure for technical transformation		10 thousand CNY	*Tra.*
Sales revenue of new products	Desirable output	10 thousand CNY	*Sal.*
Revenue from principal business		100 million CNY	*Bus.*
Industrial CO_2 emissions	Undesirable output	10 thousand tons	*Car.*
Industrial pollutant emission		10 thousand tons	*Pol.*

yet been released, this paper uses the reference framework set out in the 2006 IPCC Guidelines to estimate CO_2 emissions. The details are given in Formula (9) can refer to Du, Liu, and Diao (2019).

$$CO_2 = \sum_{i=1}^{8} EN_i \times NCV_i \times CEF_i \times COF_i \times \left(\frac{44}{12}\right) \tag{9}$$

Besides, we select five environmental pollution indicators (industrial SO_2, nitrogen dioxide, smoke and dust, wastewater, and solid wastes) and exploit the entropy method to calculate the regional pollutant emissions.

4.3. Indicator description

Table 2 provides the descriptive statistics for initial input, intermediate, additional input, desirable and undesirable outputs during 2011–2017. The Pearson correlation coefficients are presented in Table 3. The majority of coefficients between input and output indicators are positive and comparatively high, maintaining a close relationship between inputs and outputs. The coefficients between *Car.* and *Pat.*, *Inv.*, *Pro.* are relatively low, but in keeping with the variable selection of existing papers (Du, Liu, and Diao 2019; Qian, Wang, and Xiao 2018), we still choose these indicators.

5. Empirical analysis

5.1. Comparison of different network DEA models

Table 4 and the last column of Table 5 list the efficiencies evaluated by the NCCR, NSBM, NEBM, and two-stage DEA models (Kao and Hwang 2008). The two-stage DEA produces a radial measure without considering the additional inputs. Thus, the result of the two-stage DEA differs significantly

Table 2. Descriptive statistics of the indicators from 2011 to 2017.

Variable	Mean	Std.dev.	Min	Max	Median
Exp.	82843.12	107354.32	1285.00	457342.00	47670.50
Per.	411419.16	515900.54	8307.23	2462883.23	245589.67
Pat.	20182.38	30305.89	168.00	199293.00	9838.50
Inv.	16855.56	34103.84	87.00	289238.00	6141.00
Pro.	11998.79	16516.91	94.00	103149.00	7082.50
Dev.	2160789.53	2747251.39	28780.42	11824447.00	1116787.53
Tra.	281780.57	248519.54	2601.47	1368327.27	205936.53
Sal.	31778181.30	38625597.01	71661.55	148421107.00	21443673.49
Bus.	26483.65	26308.11	1351.90	107030.09	17053.90
Car.	38160.90	25833.91	4664.09	146787.32	31523.92
Pol.	36975.77	28074.82	3285.15	144506.66	30558.48

Table 3. Input-output correlations.

	Pat.	Inv.	Pro.	Sal.	Bus.	Car.	Pol.
Exp.	0.945	0.876	0.925				
Per.	0.966	0.841	0.955				
Pat.				0.918	0.838	0.442	0.843
Inv.				0.775	0.701	0.367	0.782
Pro.				0.938	0.866	0.492	0.820
Dev.				0.979	0.934	0.572	0.877
Tra.				0.821	0.847	0.604	0.718

Note: All correlation coefficients are statistically significant at the 1% level (2-tailed).

from the others. Besides, the overall efficiency is measured by the product of the efficiency values of two sub-stages, which underestimates the efficiency values and makes it somewhat unreasonable.

Figure 3 displays the kernel density graphs of the model validation results. For the NCCR models, the key shortcoming is the disregard of the effect of nonradial slacks on performance evaluation. For the NSBM model, the projected DMU may lose the proportionality because the slack is not necessarily proportional to the inputs and outputs. As shown in Figure 3, the average GTI efficiencies evaluated by the two-stage DEA, NSBM, NEBM, and NCCR models are 0.489, 0.734, 0.817, and 0.819, respectively.

5.2. Efficiency analysis and dynamic evolution

5.2.1. Correlations of overall and sub-process efficiencies

As there is a two-year lag exists in the GTI process, we get the overall GTI efficiencies and its stage efficiencies from 2011 to 2015 on the basis of data obtained in the 2011–2017 timeframe. Table 5

Table 4. Green technology innovation efficiencies of different models.

	Network CCR			Network SBM			Two-stage DEA		
Province	Overall	Stage 1	Stage 2	Overall	Stage 1	Stage 2	Overall	Stage 1	Stage 2
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	0.350	0.981	0.357
Tianjin	0.857	0.713	1.000	0.838	0.675	1.000	0.694	0.937	0.754
Hebei	0.754	0.516	0.994	0.724	0.489	0.953	0.513	0.634	0.807
Shanxi	0.522	0.343	0.744	0.316	0.302	0.430	0.338	0.665	0.516
Inner Mongolia	0.627	0.255	1.000	0.621	0.241	1.000	0.861	0.861	1.000
Liaoning	0.791	0.582	1.000	0.605	0.529	0.629	0.444	0.609	0.728
Jilin	1.000	1.000	1.000	1.000	1.000	1.000	0.299	0.613	0.518
Heilongjiang	0.477	0.352	0.662	0.281	0.235	0.418	0.364	0.885	0.407
Shanghai	0.917	0.834	1.000	0.890	0.780	1.000	0.486	0.653	0.734
Jiangsu	0.860	0.720	1.000	0.845	0.691	1.000	0.610	0.610	1.000
Zhejiang	1.000	1.000	1.000	1.000	1.000	1.000	0.293	0.608	0.440
Anhui	1.000	1.000	1.000	1.000	1.000	1.000	0.306	0.652	0.515
Fujian	0.749	0.512	0.989	0.686	0.429	0.899	0.485	0.598	0.820
Jiangxi	0.895	0.789	1.000	0.884	0.768	1.000	0.596	0.699	0.897
Shandong	0.799	0.597	1.000	0.773	0.547	1.000	0.713	0.713	1.000
Henan	0.688	0.376	1.000	0.673	0.346	1.000	0.609	0.668	0.927
Hubei	0.705	0.554	0.888	0.598	0.489	0.757	0.495	0.560	0.889
Hunan	0.789	0.664	0.936	0.583	0.585	0.587	0.341	0.371	0.942
Guangdong	1.000	1.000	1.000	1.000	1.000	1.000	0.413	0.940	0.430
Guangxi	0.652	0.665	0.729	0.437	0.440	0.503	0.478	0.620	0.786
Hainan	1.000	1.000	1.000	1.000	1.000	1.000	0.557	0.679	0.878
Chongqing	0.979	0.959	1.000	0.975	0.949	1.000	0.322	0.495	0.614
Sichuan	0.999	0.997	1.000	0.989	0.979	1.000	0.241	0.697	0.336
Guizhou	0.698	0.769	0.731	0.467	0.722	0.441	0.699	0.814	0.847
Yunnan	0.870	0.903	0.885	0.681	0.832	0.671	0.435	0.923	0.497
Shaanxi	0.624	0.598	0.729	0.418	0.546	0.476	0.672	0.751	0.855
Gansu	0.763	0.546	0.984	0.609	0.484	0.756	0.322	0.629	0.541
Qinghai	0.938	0.875	1.000	0.932	0.863	1.000	0.364	0.779	0.509
Ningxia	0.913	0.893	0.952	0.712	0.773	0.688	0.679	0.964	0.688
Xinjiang	0.703	0.777	0.733	0.487	0.538	0.572	0.712	0.805	0.874

Table 5. Green technology innovation efficiencies of 30 provinces in China.

Province/Year	2011	2012	2013	2014	2015	Average
Beijing	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	0.866	0.896	0.892	0.826	0.801	0.856
Hebei	0.741	0.738	0.791	0.773	0.726	0.754
Shanxi	0.505	0.570	0.510	0.490	0.515	0.518
Inner Mongolia	0.627	0.647	0.619	0.622	0.622	0.627
Liaoning	0.754	0.829	0.801	0.728	0.831	0.788
Jilin	1.000	1.000	1.000	1.000	1.000	1.000
Heilongjiang	0.437	0.487	0.505	0.480	0.454	0.472
Shanghai	0.896	0.924	0.937	0.928	0.896	0.916
Jiangsu	0.901	0.851	0.849	0.866	0.831	0.859
Zhejiang	1.000	1.000	1.000	1.000	1.000	1.000
Anhui	1.000	1.000	1.000	1.000	1.000	1.000
Fujian	0.716	0.731	0.753	0.749	0.789	0.747
Jiangxi	0.754	0.877	0.910	0.931	1.000	0.894
Shandong	0.753	0.813	0.821	0.820	0.782	0.798
Henan	0.662	0.724	0.692	0.693	0.667	0.688
Hubei	0.669	0.699	0.714	0.709	0.722	0.703
Hunan	0.819	0.801	0.761	0.786	0.747	0.783
Guangdong	1.000	1.000	1.000	1.000	1.000	1.000
Guangxi	0.562	0.726	0.651	0.619	0.672	0.646
Hainan	1.000	1.000	1.000	1.000	1.000	1.000
Chongqing	0.926	0.970	1.000	1.000	1.000	0.979
Sichuan	1.000	1.000	0.999	1.000	0.992	0.998
Guizhou	0.712	0.686	0.672	0.703	0.697	0.694
Yunnan	0.802	0.779	0.742	1.000	1.000	0.865
Shaanxi	0.734	0.676	0.620	0.537	0.530	0.620
Gansu	0.789	0.778	0.820	0.724	0.675	0.757
Qinghai	1.000	1.000	1.000	0.687	1.000	0.937
Ningxia	1.000	0.908	0.891	0.956	0.767	0.904
Xinjiang	0.623	0.725	0.709	0.770	0.667	0.699

shows the average GTI efficiencies. We can also derive the average green technology R&D (GTR) efficiencies, and average technology achievement transformation (TAT) efficiencies of each year from 2011 to 2015.

Table 6 shows the Spearman rank correlation tests. The significant correlations suggest that overall efficiency is linked to the two-stages and also indicate that overall efficiency is more connected with stage 1 than to stage 2. That means the GTR stage, which is in line with the analysis

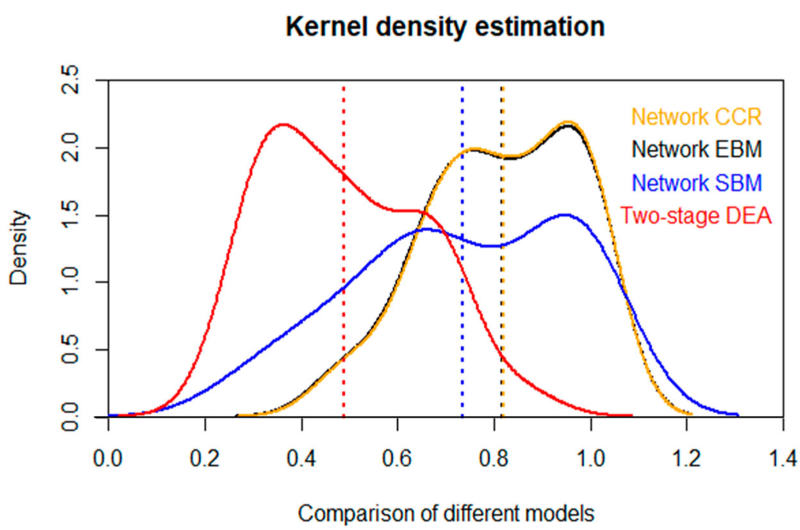

Figure 3. Kernel density graphs of the evaluation results of different models.

Table 6. Spearman rank correlation tests of overall and sub-process efficiencies.

Efficiency	Overall	Stage 1	Stage 2
Overall	1.0000		
Stage 1	0.8987***	1.0000	
Stage 2	0.7101***	0.4543***	1.0000

Note: ***Indicates that correlations are statistically significant at the 1% level (2-tailed).

of Du, Liu, and Diao (2019) and Qian, Wang, and Xiao (2018), is the major cause for inefficiency in the GTI process. That is, the GTR stage has a greater capacity for quality gain in the provinces of China, although the efficiency of the TAT stage is also important. The lower values and the weaker statistical significance for the association between the two sub-stages mean that the two sub-stages are not statistically related.

5.2.2. Distributions of overall and sub-process efficiencies

The average overall efficiencies for each province are derived from the results listed in the last column of Table 5 and illustrated in Figure 4. We divide the average overall efficiency values into four intervals, tagged as efficient values (equal to 1.00), high-efficiency values (between 0.80 and 0.99), medium-efficiency values (between 0.60 and 0.79), and low-efficiency values (less than 0.60).

Seeing from Figure 4, the average overall GTI efforts of Beijing, Jilin, Anhui, Zhejiang, and Guangdong are efficient, which means they have optimal performance in GTI activities. In contrast, Shanxi and Heilongjiang are comparatively poor in terms of overall GTI efficiencies, which indicates these two provinces face severe inefficiency in their GTI activities.

To analyse the specific reasons for inefficiency in terms of regional GTI activities in China, Figure 5 shows a scatter diagram based on the average values of the GTR efficiencies (0.725) and the TAT efficiencies (0.929) of the 30 provinces. The scatter diagram is divided into four quadrants, tagged as I, II, III, and IV.

Figure 4. Average value of the overall efficiencies of 30 provinces in China.

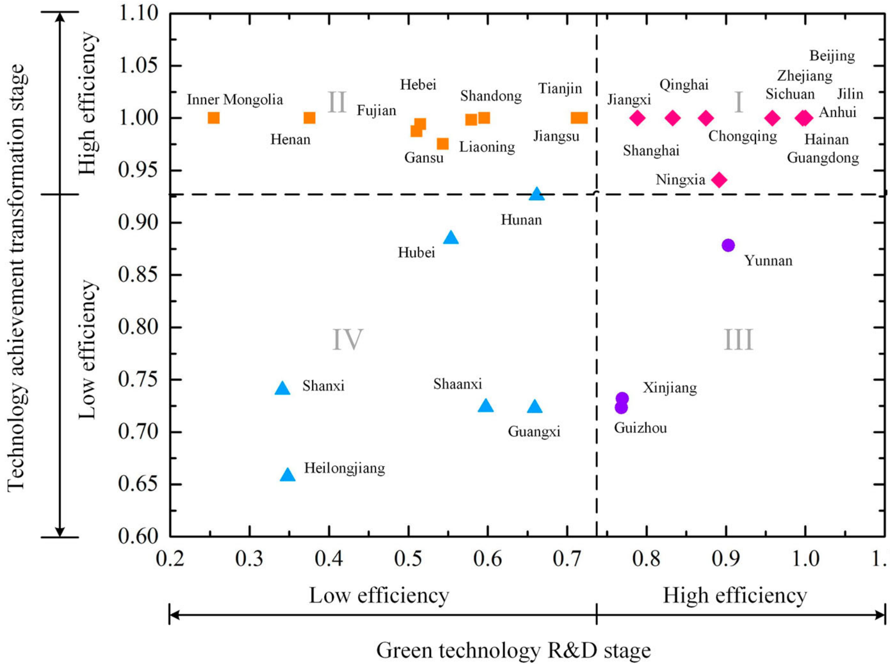

Figure 5. Decomposition chart of provinces based on two-stage efficiencies.

5.2.3. Variations of overall and sub-process efficiencies

Considering the geographical location and economic development, we divide the provinces into Eastern, Central and Western regions according to the Chinese government's official definition.

Figure 6 reveals the variations of the average GTI efficiencies, GTR efficiencies, and TAT efficiencies in the divided three regions. It is concluded that the eastern region has relatively high average overall and sub-process efficiencies, while the central region and western region have relatively low overall and sub-process efficiencies. However, we note disparities between the central and western areas, given the efficiencies of the sub-process. These findings are generally consistent with the geographic distribution of the degree of economic growth (Liu et al. 2019).

The average GTI efficiency in the overall region (i.e. China) (0.817) is between the GTR efficiency (0.725) and the TAT efficiency (0.929). As presented in Figure 6(b) and (c), the average efficiencies of the GTR stage are greatly fluctuating, with comparatively high and stables average efficiencies in the

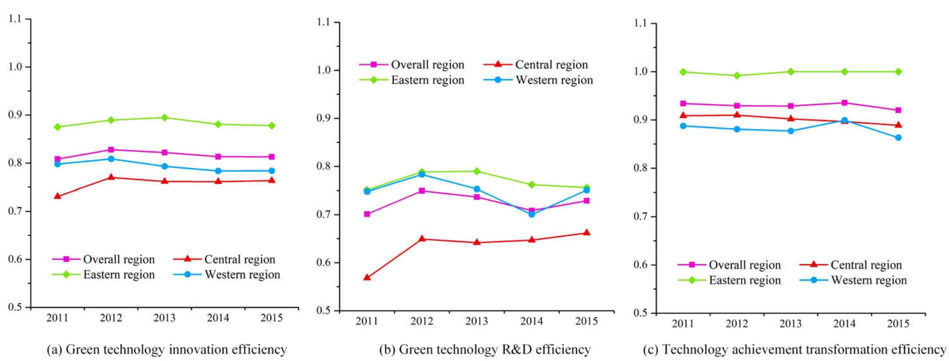

Figure 6. Variation of average efficiencies for regions.

Table 7. MML index of overall and two stages.

Stage	Region	2011–2012	2012–2013	2013–2014	2014–2015
GTI	Overall	1.009	0.980	1.001	1.128
	Eastern	0.971	0.985	0.990	1.110
	Central	1.074	0.935	1.014	1.076
	Western	0.998	1.006	1.003	1.183
GTR	Overall	1.080	0.963	0.964	1.249
	Eastern	0.981	0.993	0.963	1.170
	Central	1.246	0.887	1.000	1.183
	Western	1.058	0.989	0.939	1.376
TAT	Overall	0.989	0.999	1.015	1.064
	Eastern	0.974	0.990	1.004	1.055
	Central	1.006	0.988	1.016	1.024
	Western	0.992	1.017	1.026	1.104

TAT stage. The variation of average overall efficiency is mostly attributed to the GTR stage, which contradicts the studies of Liu et al. (2019).

5.3. Meta-frontier ML index and its decomposition

5.3.1. MML index analysis of China's GTI

This paper develops a network EBM model and then constructs the MML performance index of GTI. Table 7 shows the MML index of regional GTI from 2011 to 2015, while Figure 7 shows the accumulated MML index.

According to Table 7, the MML indexes of GTI activities in each sub-process and region are all above 1, which indicates that there was an improvement in overall and sub-process GTI efficiencies during 2014–2015. From the view of the whole country, the annual MML index of the overall GTI varies between 0.980 and 1.128, with an average annual growth of 2.8%.

According to Figure 7, the MML index of GTI has risen at both the aggregate and regional levels. The MML index has risen most in the west region, while it has improved least in the central region. As shown in Figure 7(a), the variation of MML index in the overall GTI is well balanced. The MML index in the GTR stage (see Figure 7(b)) fluctuates considerably, while in the TAT stage (see Figure 7(c)), it remains highly stable.

Based on Model (6), we decompose the MML index of GTI activities into three indexes: *EC*, *BPC*, and *TGC*. Decomposing the MML index provides a clearer explanation of the reasons why the GTI performance varies dynamically.

The results in Figure 8 show that the accumulated *BPC* value has an obvious upward trend with little fluctuation. The accumulated *BPC* values in overall GTI, the GTR stage, and the TAT stage are 1.105, 1.193, and 1.064, respectively. Thus, the change of technological progress must be the primary explanation for the improvement of the MML index. The *TGC* indexes decreased slightly in the overall GTI. The average distance between group and meta-frontier increases is obvious. A

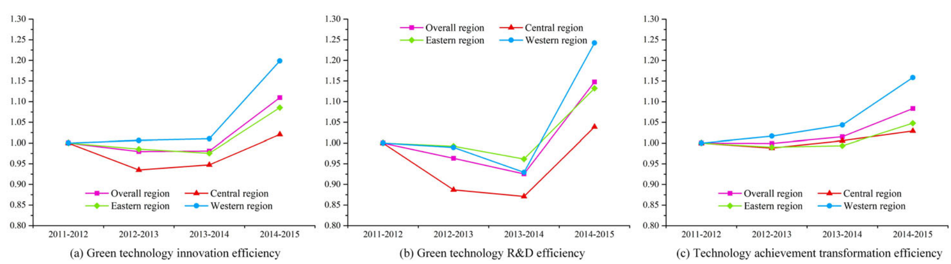

Figure 7. Accumulated MML index of different regions in China.

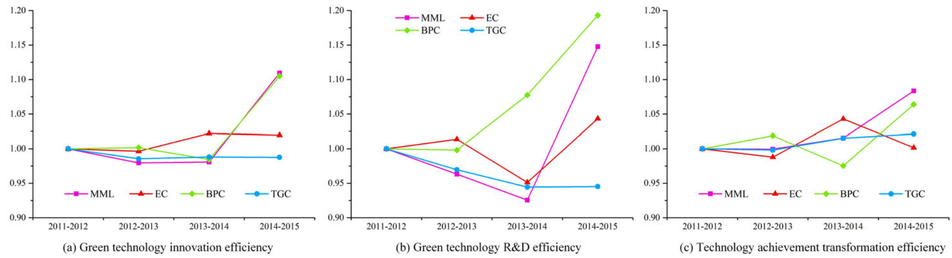

Figure 8. National accumulated MML index and its decomposition.

sharp drop in the *TGC* index is shown in Figure 8(b), while a slight increase is shown in Figure 8(c). These changes indicate that the technological catch-up effect is obvious in the TAT stage.

5.3.2. Regional MML index decomposition and comparison

GTI operations have diverse characteristics because of their geographic heterogeneity, as do the factors that cause GTI's dynamic shifts. As shown in Figure 9, technological progress changes are the key factors that lead to improving the MML index of the overall and sub-process GTI in eastern region. The accumulated technological catch-up effect increases in the overall and sub-process GTI, especially in the GTR stage. The increase is seen by reducing the average distance in GTR stage between the group and meta-frontier. This change also affects the technological catch-up effect in the overall GTI. Also, the accumulated technical efficiency changes decrease in the overall and sub-process GTI, especially in the GTR stage. These changes indicate that improving the managerial level of GTI activities is also vital, especially the management of R&D activities.

As shown in Figure 10, technological progress changes are the key factors that lead to improving the MML index of the overall and sub-process GTI in central region. The accumulated technological catch-up effect decreases in the overall and sub-process GTI, especially in the GTR stage. The decrease is suggested by the expansion of the average distance in the GTR stage between group-

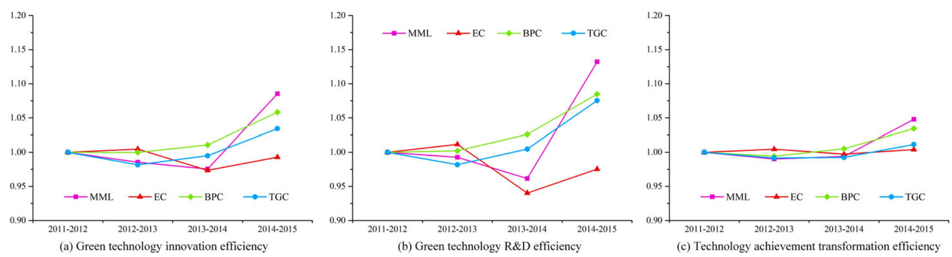

Figure 9. Eastern region accumulated MML index and its decomposition.

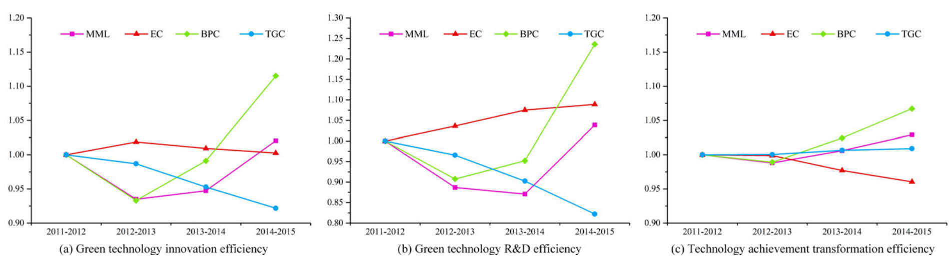

Figure 10. Central region accumulated MML index and its decomposition.

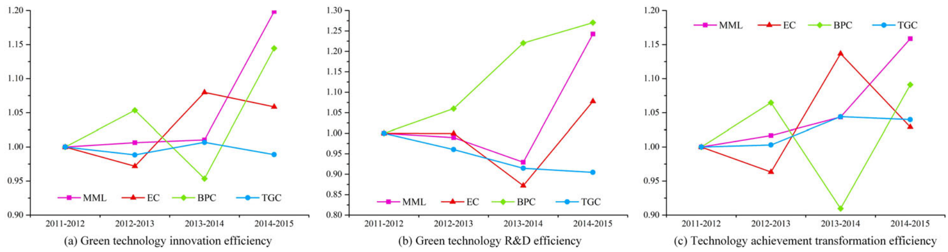

Figure 11. Western region accumulated MML index and its decomposition.

boundary and meta-boundary. This change also affects the technological catch-up effect in the overall GTI. Also, the accumulated technical efficiency changes increase in the GTR stage, while they decrease in the TAT stage. These changes indicate that improving the managerial level in the TAT stage is essential.

As shown in Figure 11, technological progress changes are the key factors that lead to improving the MML index of the overall and sub-process GTI in western region. The variations of accumulated technological progress changes and accumulated technical efficiency changes are symmetrical in overall and sub-process GTI. They fluctuate greatly in the study period and reach a higher accumulated value compared to the initial value. This change indicates that the technical and managerial levels improved slightly. Besides, the accumulated technological catch-up effect increases in the TAT stage, while it decreases in the GTR stage. These changes show that, in the GTR stage, the average distance between group and meta-frontier expands and in the TAT stage narrows.

6. Conclusions

This paper builds a comprehensive analytical framework for provincial GTI activities in China from an efficiency evaluation and productivity change viewpoint. Regional GTI efficiency and productivity change during '12th Five-Year Plan (2011–2015)' period is evaluated using the new framework. This paper draws the following conclusions from previous findings and study.

1. The findings suggest that relying on a single sub-process is not necessary to increase overall performance. It is realistic to open up internal structures and explore the causes of inefficiency in the process of GTI.
2. The Spearman rank correlation tests show that the overall efficiency is linked to performance in the two sub-processes. The GTR stage is the main explanation of inefficiency in the GTI process. The analysis also proves that the efficiencies of the two sub-processes may diverge significantly; one sub-process is often much more efficient than the other.
3. The eastern region has relatively high average overall and sub-process efficiencies, while the central and western region are relatively low. The average efficiencies in the GTR stage fluctuate greatly, while in the TAT stage, the performance are comparatively high and remain stable.
4. Overall and sub-process GTI efficiency improved significantly in 2014–2015. The major factor contributing to the improvement of the MML index in overall and sub-process GTI was technological progress. It indicates the contemporaneous benchmark technology frontier shifts to the intertemporal benchmark technology frontier.

This research has drawbacks, but they can be important reference points for future work. Firstly, this paper does not consider the competition of regional innovation system and its subsystems, because the investment of innovation resources is limited, there must be competition relationship. By introducing game theory, the relationship between GTR and TAT stage could be well measured.

Secondly, this paper ignores the modelling of shared correlation inputs in network production structures, which can be considered for further study in the future. Thirdly, this study ignores regional factors such as industrial structure, geographical location, population, and infrastructure construction, which may greatly affect GTI efficiency. In the future, we can further explore the influence of external factors on regional GTI efficiency and total factor productivity.

Disclosure statement

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