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Measuring the inefficiency of Chinese research universities based on a two-stage network DEA model

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ABSTRACT

This paper investigates the inefficiency and productivity of 64 Chinese research universities and their evolution over the recent period of 2010–2013, where the production process of each research university is described as a general two-stage network process. We first develop a general two-stage network directional distance framework with carry-over variables to gauge the universities' inefficiencies. Second, to study the evolution of the universities, we develop a Luenberger productivity indicator to measure the productivity changes over time, as well as decompositions. The empirical results show that the Luenberger productivity indicator increased significantly over the examined period. The productivity gains were primarily driven by improvements in efficiency. In other words, the efficiency increased on average over the period of 2010–2013. However, technical changes for many universities were below zero, which led to technology deterioration on average. Finally, based on the estimates, we propose several policy suggestions for improving efficiency and productivity.

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1. Introduction

In modern society, universities and colleges are social organizations and cultural institutions and play an important role in human society, economy, culture and international communication through the realization of various functions. Jaspers (1965) stated Ï[A] *University is composed of scholars and students of the truth-seeking community*.Ät the beginning of their establishment, the function of colleges and universities was more singular, primarily imparting knowledge and training specialized personnel. With the development of society, the functions of colleges and universities have been expanded and standardized, i.e., talent cultivation, scientific research and serving society have become the three main functions of modern colleges and universities. Currently, these three functions have become the consensus of the higher education system worldwide.

As in almost every country in the world, universities are also important institutions for scientific and technological achievements, particularly in China. Since the reform and open-door policy implementation in 1978 and with the country's emphasis on education and technological innovation, China has made significant efforts to improve the performance of its scientific system to reach the forefront of world research over the past several decades given the country's continuously growing financial expenditures on university education. Consequently, increasingly numerous talent is becoming involved

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in scientific research activities, and increasingly numerous scientific and technological achievements have been reached. In August 2015, the National Science Library (LAS) of the Chinese Academy of Sciences (CAS) released an official report entitled "Blue Book on China's Competitiveness in Basic Research 2015", which states that the number of SCI papers published in China amounted to more than 216,000 in 2013, approximately 62.2% as many as the United States (US) in the same year. In addition, the number of citations of papers written by researchers at Chinese universities and research institutions increased significantly. For example, the number of citations in 2012 accounted for approximately 12.4% of those of American papers, whereas the corresponding percentage was only 6.6% in 2008. In certain disciplines, such as environmental biotechnology and chemical engineering, China has surpassed the US in terms of the number of SCI publications. This success was primarily due to China's huge investment in its higher education system in recent years. OECD (2014) shows that R&D (research and development) expenditure in China has doubled from 2008 to 2012. In 2012, China's Gross Domestic Expenditure on R&D (GERD) was 257 billion US dollars.[1] In the same year, the GERDs in the US, EU-28 countries and Japan were 397 billion dollars, 28 billion dollars and 134 billion dollars, respectively. Currently, China is reorganizing its scientific system to become more competitive, and funds should be used more efficiently given the limited resources.

Johnes et al. (2017) argued that it is important for education to be provided as efficiently as possible with competing demands for government funding, and efficiency occurs when outputs from education are produced at the lowest level in terms of resources. Arguments in the same direction can be found also in, for example, Abbott and Doucouliagos (2003), Avkiran (2001), and Casu and Thanassoulis (2006). Therefore, it is of great importance to address the need for an efficiency analysis and performance evaluation of Chinese universities.

As a mathematical tool for evaluating the efficiency of multiple decision-making units (DMUs), the DEA (data envelopment analysis) approach (e.g., Banker, Charnes, & Cooper, 1984; Charnes, Cooper, & Rhodes, 1978;) is widely used in performance evaluation or analysis. The DEA avoids the influence of subjective factors on the evaluation results; therefore, it is widely used in the evaluation of scientific research efficiency worldwide. For example, the DEA has been applied in education efficiency analyses (Johnes, Portela, & Thanassoulis, 2017). While most conventional DEA models treat the operation of a DMU as a "black box" (Färe & Grosskopf 2000; Kao & Hwang, 2008), some recent research intends to go inside the "black box" and the internal structure of the DMUs (Tone & Tsutsui, 2009). For example, network DEA models have been developed in recent years to consider the process within a DMU, which can include several sub-processes or stages. Every stage is characterized by its own inputs and outputs and is related to other stages through intermediate flows (Färe & Grosskopf, 2000).

A university's scientific research activity is a complex process of multiple inputs, internal processes, and multiple outputs. There are several Input-Process-Output (IPO) models that have been extensively used to describe the influences of team effectiveness of production units (see, e.g., West Borrill, & Unswort, 1998). Brandt and Schubert (1997) augmented the IPO model, taking into account the production technology determining the process by which inputs are transformed into outputs. Their IPO model depicts inputs, processes and outputs as three interrelated variable complexes. However, our literature survey shows that most of the studies conducted through a DEA are at the static level and not at the dynamic level of multi-stage scientific research productivity; see the literature review in detail in Section 2. This point can be twofold. First, there are few studies on university efficiency that have focused on a two-stage network DEA model with carryover variables. Second, according to the IPO model, it is important to open the process between inputs and outputs by treating universities as a two-stage network process instead of merely a "black box" to portray the internal activities inside universities.

While we believe that DEA is a desirable approach for university efficiency evaluation, the traditional or black box DEA has not been incorporated into the internal structure that exists at a DMU. Motivated by the coping strategies for this limitation, this paper aims to investigate the inefficiency and productivity of 64 Chinese research universities and their evolution over the recent period of 2010–2013, where the production process of each research university is described as a general two-stage network process with feedback between two stages, where the feedback variable produced at the second stage of a previous year (a portion of total income (TI) in our study. See Section 4.1) goes into the first stage of the current year. To this end, we develop a general two-stage network directional distance framework with carryover variables to measure the universities' inefficiencies and a Luenberger productivity indicator to measure the productivity changes over time, as well as decompositions of the indicator for the examined universities. It should be noted that in this study, we assume that the technology transfer revenue is used to support research and development (R&D) outputs and technology services; hence, these are the input of the first stage of university production.

The remainder of the paper is organized as follows: Section 2 briefly summarizes the existing literature on university performance measurements and describes the two-stage process of a university. Section 3 sets up the mathematical basis for the analysis and defines a two-stage network directional distance (NDD) measure for gauging the efficiency of representative Chinese research universities, as well as a Luenberger productivity indicator for productivity changes over time. In Section 4, we show the details of the input and output variables used in this paper and their data source as well as the corresponding descriptive statistics. A case study on 64 Chinese research universities over the period 2009–2013, along with policy implications and suggestions, follows in Section 5. Finally, Section 6 offers a discussion and presents the study's conclusions.

[1] Hereafter, monetary figures refer to dollars at purchasing power parity in 2005.

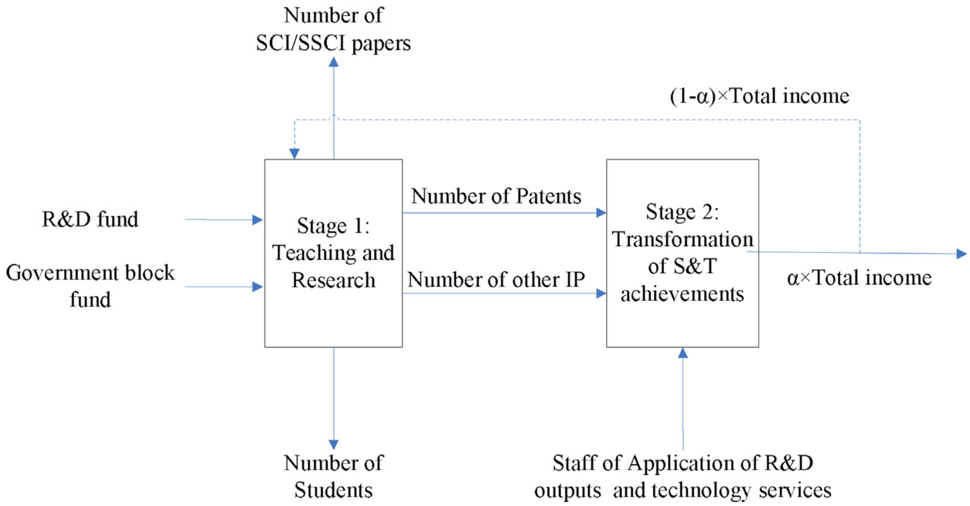

Fig. 1. Two-stage network process of universities.

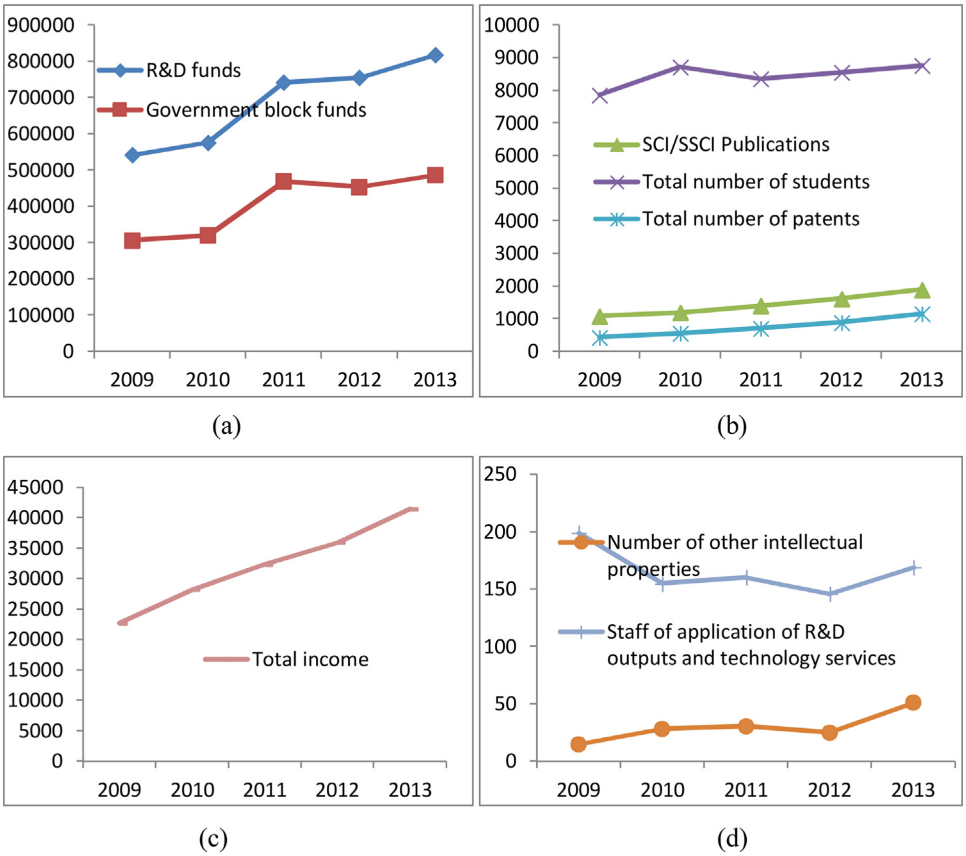

Fig. 2. Changes in the average value of input and output variables.

2. The literature review and our conceptual model

2.1. Education efficiency in a DEA framework

Education efficiency has been the concern of research in recent decades. Frontier estimation techniques lead to the expansion of literature on education efficiency (Johnes et al., 2017). DEA (see, e.g., Banker et al., 1984; Charnes et al., 1978) and SFA (Stochastic frontier analysis) (see, e.g., Aigner, Lovell, & Schmidt, 1977; Battese & Corra, 1977) are the two most commonly used Frontier estimation techniques, which can be used to estimate cost functions or production frontiers of DMUs, from which efficiency estimates can be derived. In this subsection, we focus our literature review on DEA in education.

The DEA approach, whose name was coined by Charnes et al. (1978), is an increasingly popular mathematical programming methodology used to assess the relative efficiency of DMUs with multiple inputs and outputs. The essence of the standard DEA is to find a projection point on the production frontier first and later to evaluate the DMUs on the frontier as efficient. The DMUs that are not efficient are compared with their peers or projections on the frontier to gauge their efficiencies. Traditionally, DEA-related research treats the operation or production process of a DMU as a "black box.Ḧowever, recent research intends to go inside the black box and implement the internal structure of the DMUs (see, e.g., Färe & Grosskopf, 2000; Tone & Tsutsui,2009). For example, network DEA models have been developed to consider the production process within a DMU, which can include several sub-processes or stages. Every stage is characterized by its own inputs and outputs and is related to other stages through intermediate flows (Färe & Grosskopf, 2000). Other research related to network DEA can be found in papers such as Chen and Zhu (2004), Liang, Cook, and Zhu (2008), Chen, Cook, Li, and Zhu (2009), Chen, Liang, and Zhu, (2009), Cook, Zhu, Bi, and Yang (2010), and Sahoo, Zhu, Tone, and Klemen (2014).

There are many DEA-based education efficiency studies in the existing literature, which can be categorized roughly into three groups: (a) efficiency measurement based on black box DEA, (b) measurement of productivity changes using black box DEA, and (c) measurement of efficiency and productivity changes using network DEA.

2.1.1. The first stream of research confines itself to an efficiency assessment using traditional black box DEA

Within this group, traditional black box DEA is used to measure technical, scale and cost efficiencies or benchmarking. Avkiran (2001) used DEA to examine the relative efficiency of Australian universities based on three performance approaches, including overall performance, performance on delivery of educational services, and performance on fee-paying enrolments. Fandel (2007) measured the performance of universities in North Rhine-Westphalia, Germany. Deluyi, Rashed, Sofian, and Daud (2014) measured the efficiency of 16 faculties and institutes at the Ferdowsi University of Mashhad in Iran. Nkonki, Ntlabathi, and Ncanywa (2014) measured the efficiency of the programme, faculties, and the institution in a selected university and concluded that there are variations in the efficiency levels of faculties and programmes. Abramo, Cicero, and D'Angelo (2011) measured the technical efficiency of research activities using bibliometric data on the Italian university system. Rosenmayer (2014) compared the appropriateness and adequacy of several DEA studies documented in the existing literature dealing with the effectiveness of universities. Larrán-Jorge and García-Correas (2015) investigated the efficiency of 47 Spanish national universities using the dimensions of teaching, research, and transfer of knowledge efficiency and compared the authors' DEA result with those of the financial approaches used by the universities.

Kao and Hung (2008) applied the assurance region DEA method to evaluate the relative efficiency of the academic departments at the National Cheng Kung University in Taiwan. Herrero and Algarrada (2010) used a modified DEA model to distinguish managerial efficiency from educational programme efficiency. Ho (2015) used DEA and AHP (Analytic Hierarchy Process) to compare the efficiency among universities in Taiwan and around the world. Within this group, the key point is to select appropriate variables to reflect the input-output process of universities' activities to use DEA as the gauging tool to measure their relative efficiencies. In the DEA framework, Haelermans and Ruggiero (2017) introduced a non-parametric measure of the cost of adequacy that controls for the socio-economic environment and resource prices to analyse the estimates of the cost of adequacy of Dutch schools. Similar studies can be found in Abbott and Doucouliagos (2003), Ferrari and Laureti (2005), Johnes (2006a,b), Casu and Thanassoulis (2006), Giménez and Martínez (2006), Chang, Wu, Ching, and Tang (2009), Katharaki and Katharakis (2010), Kong and Fu (2012), Ramírez and Alfaro (2013), and Inua and Maduabum (2014).

DEA can also be used as a performance benchmarking tool in higher education systems. For example, Caballero, Galache, Gómez, Molina, and Torrico (2004) proposed a DEA-based methodology to serve as a guiding mechanism for the allocation and management of university financial resources, taking efficiency as the objective. Ruiz, Segura, and Sirvent (2015) developed a minimum distance DEA model that provides the closest targets for use when expert preferences are incorporated into the analysis to benchmark and set targets and evaluated the educational performance of public Spanish universities.

2.1.2. The second stream of research conducts a cross-period analysis using traditional black box DEA

Taylor and Harris (2004) assessed the technical efficiency of South African universities between 1994 and 1997. Johnes and Yu (2008) examined the relative efficiency of 109 regular Chinese universities with respect to research accomplishments for 2003 and 2004. Abramo et al. (2011) measured the technical and allocative efficiency of university research activity based on bibliometric data of the Italian university system over the period 2004–2008. Sagarra, Mar-Molinero, and Agasisti (2017) combined the traditional rankings ratios and DEA models and applied the method to the official statistics of 55 universities over a six-year period (2007–2012). Sagarra et al. (2017) combined the traditional ratio approach and DEA models to measure the efficiency changes of 55 Mexican universities over the period 2007–2012. Schubert and Yang (2016) investigated the evolution of scale efficiency and optimal operation size of German research universities using the traditional DEA model over the period of 2000–2011. Parteka and Wolszczak-Derlacz (2013) examined patterns of productivity change based on a large set of 266 public higher education institutions in 7 European countries in the period 2001–2005 using a bootstrapped DEA-Malmquist productivity index. Several other higher education studies assessing productivity changes over time can be found in, for example, Flegg, Allen, Field, and Thurlow (2004), Johnes (2008), Worthington and Lee (2008), Agasisti and

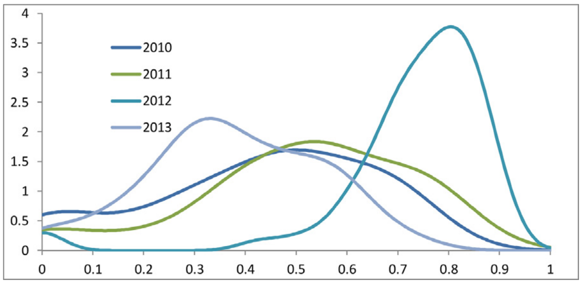

Fig. 3. Truncated kernel density graphs of the NDD value in four separate years.

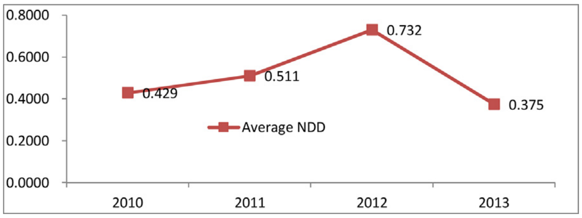

Fig. 4. Trend of the average value of NDD over the examined period.

Johnes (2009), and Agasisti and Pérez-Esparrells (2010). In this group, the primary feature is to investigate efficiency or productivity using panel data to study the cross-period efficiency measurement.

Johnson and Ruggiero (2014) extended the nonparametric DEA approach to decompose the Malmquist Productivity Index (MPI) suggested by Färe, Grosskopf, Norris, and Zhang (1994) into a change in technical efficiency, technology and environmental efficiency, and they used this approach to analyse the educational production of Ohio school districts. Subsequently, this approach was extended by Brennan, Haelermans, and Ruggiero (2014) to the more general case of variable returns to scale to decompose the MPI into a change in technical, scale and environmental efficiency.

2.1.3. The third stream of research goes inside the black box and investigates the efficiency of universities using network DEA

As shown above, while the research in the first and second groups treats the operation of a DMU as a black box, recent research attempted to go inside the black box and implement the internal structure of DMUs. Along this line, Rayeni and Saljooghi (2010) used network DEA to estimate efficiency and examine the impact of each variable on the efficiency and productivity changes of the universities in the Sistan and Baluchistan states in Iran for the period 2004–2009. Lu (2012) used a two-stage network DEA to evaluate the cost, teaching and research efficiencies of public universities in Taiwan, as well as a truncated regression to discuss whether intellectual capital affects the operating efficiency of universities. Chang, Chung and Hsu (2012) constructed a two-stage network DEA model comprising the first stage of research and development performance and the second of teaching performance for 34 tourism and leisure departments in Taiwanese universities. Lee and Worthington (2016) developed a network DEA model capturing both the quality and quantity attributes to assess the quality of research in Australian universities.

Most of the research works in the third group consider the activities of universities within a single period instead of multiple periods and/or use static network DEA without implementing dynamic variables that are carried over from a previous period to a current period. See the logic model of universities specified in Section 2.2.

The above survey findings indicate that there are few significant efficiency/productivity studies that aim to provide policy suggestions for the current Chinese university system within an appropriate two-stage network DEA framework with a carryover variable, which, we believe, plays an important role in the development of the system. We fill this gap in the literature by investigating the efficiency and productivity change of 64 Chinese research universities by using the recent 2010–2013 data. In this study, the carryover variable has as its proxy a part or fixed portion of the revenue from the sale of patents by universities.

2.2. University as a two-stage process

As discussed in the introduction, the three main functions of colleges and universities have been recognized as talent cultivation, scientific research and serving society, which have become the consensus of the higher education system worldwide. Park (1996) noted that teaching, research, and the application of research and development (R&D) and technology services are the three main criteria primarily considered by a university for tenure and promotion. Following the IPO model in, for example, Brandt and Schubert (1997), and considering the three main functions of colleges and universities, we model a Chinese university as the entity transforming different types of staff and research funding into multiple outputs. Therefore, we formulate the production system of a university as a two-stage system (see Fig. 1).

In the first stage, which involves teaching and research, we use a research and development (R&D) fund (which is mainly used for R&D) through research projects and a government fund (which is mainly used for teaching) to a university as the initial inputs of the university. The outputs of the first stage include the number of SCI/SSCI papers, number of students, number of patents, and number of other intellectual properties. Among these four outputs in the first stage, patents and other intellectual properties are further used as the two inputs into the second stage, which are featured as the transformation of science and technology (S&T) achievements. The third input going into the second stage is the staff working for the application of R&D outputs and technology services. The single output of the second stage is TI (total income) from Stage 2, which equals the technology transfer (TT) revenue and income from the sale of patents. In this stage, there is one coefficient, α, which is the proportion of TI because a part of this output will be the input in the first stage. The coefficient α is determined by the government policy makers.

3. Two-stage network DEA model

We formulate a Chinese university decision-making problem for a two-stage network process according to Fig. 1. At stage 1 in year t, each university converts a carryover vector, $c^{t-1} \in \Re_+$, produced from a previous year, and an exogenous input vector, $\mathbf{x}^{1,t} \in \Re_+^2$, into an intermediate-product vector, $\mathbf{z}^t \in \Re_+^2$ and a final output $\mathbf{y}^{1,t} \in \Re_+^2$. At stage 2, the university uses $\mathbf{z}^t$ as an intermediate input and $x^{2,t} \in \Re_+$ as an exogenous input to convert it into two outputs: a carryover $c^t \in \Re_+$ to be used at stage 1 in the next period and a final output, $y^{2,t} \in \Re_+$. Note that $c^{t-1}, x^{2,t}, y^{2,t}$ and c^t are singletons.

A production possibility set for stage 1 in period t is defined by

$$T^{1,t} = \left\{ \left(c^{t-1}, x^{1,t}, y^{1,t}, z^t\right) \mid \left(x^{1,t}, y^{1,t}, z^t\right) \text{ is feasible for fixed} c^{t-1} \right\}. \quad (1)$$

The period t stage 1 production possibility set is the set of carryover from the preceding period and exogenous inputs in the current period, as well as the intermediate outputs. The year t stage 2 production possibility set is denoted as

$$T^{2,t} = \left\{ \left(\mathrm{z}^t, x^{2,t}, y^{2,t} + c^t\right) \mid \left(\mathrm{z}^t, x^{2,t}, y^{2,t}, c^t\right) \text{ is feasible} \right\}. \quad (2)$$

The period t stage 2 production possibility set is the set of all intermediate products and exogenous inputs in the current period to produce final outputs in the current period and carryovers to be used in the subsequent period. We assume that stage 2 decides on the final output and carryover associated with the total revenue from TT and selling patents:

$$y^{2,t} + c^t \quad (3)$$

3.1. Two-stage network directional distance measure

In this subsection, we present a nonparametric DEA framework. We assume there are $j = 1, \ldots, J$ universities. Let $\boldsymbol{\lambda}^{1,t} = (\lambda_1^{1,t}, \ldots, \lambda_J^{1,t}) \in \Re_+^J$ and $\boldsymbol{\lambda}^{2,t} = (\lambda_1^{2,t}, \ldots, \lambda_J^{2,t}) \in \Re_+^J$ be the activity or intensity vectors associated with stages 1 and 2, respectively. Throughout the paper, all input-output observations, c_j^{t-1} $(\forall j, \forall t-1)$, $x_{n,j}^{1,t}$ $(\forall n, \forall j, \forall t)$, $x_{n,j}^{2,t}$ $(\forall n, \forall j, \forall t)$, $y_{mj}^{1,t}$ $(\forall m, \forall j)$, $y_j^{2,t}$ $(\forall j, \forall t)$, $z_{q,j}^t$ $(\forall q, \forall j, \forall t)$, c_j^t $(\forall j, \forall t)$, are assumed to be positive, where subscript 'j' indicates an observation for university j. We implement Eq. (3) as follows:

$$y_o^{2,t} + c^t \le \sum_{j=1}^{J} \left(y_j^{2,t} + c_j^t\right) \lambda_j^{2,t} \quad (4)$$

which adapts the constraints used for different industries by Färe, Grosskopf and Margaritis (2011) and Fukuyama and Weber (2015). Note that c^t is an endogenous variable in model (5).

Building on Akther, Fukuyama and Weber (2013) and Fukuyama and Weber (2015), a two-stage network directional distance measure corresponding to Fig. 1 takes the following form:

$$NDD^t \left(c_o^{t-1}, \mathbf{x}_o^{1,t}, \mathbf{y}_o^{1,t}, \mathbf{x}_o^{2,t}, \mathbf{y}_o^{2,t}; \mathbf{g}_x^1, \mathbf{g}_y^1, g_x^2, g_y^2\right) = \max \beta$$

subject to

$$\begin{aligned}
& c_o^{t-1} \ge \sum_{j=1}^{J} c_j^{t-1} \lambda_j^{1,t}, \quad \mathbf{x}_o^{1,t} - \beta \mathbf{g}_x^1 \ge \sum_{j=1}^{J} \mathbf{x}_j^{1,t} \lambda_j^{1,t}, \ \mathbf{y}_o^{1,t} + \beta \mathbf{g}_y^1 \le \sum_{j=1}^{J} \mathbf{y}_j^{1,t} \lambda_j^{1,t}, \quad \mathbf{z}^t \le \sum_{j=1}^{J} \mathbf{z}_j^t \lambda_j^{1,t}, \\
& \mathbf{z}^t \ge \sum_{j=1}^{J} \mathbf{z}_j^t \lambda_j^{2,t}, \quad x_o^{2,t} - \beta g_x^2 \ge \sum_{j=1}^{J} x_j^{2,t} \lambda_j^{2,t}, \ y_o^{2,t} + \beta g_y^2 + c^t = \sum_{j=1}^{J} \left(y_j^{2,t} + c_j^t\right) \lambda_j^{2,t}, \\
& \mathbf{z}^t \ge \mathbf{0}, c^t \ge 0, \boldsymbol{\lambda}^{1,t} \ge \mathbf{0}, \boldsymbol{\lambda}^{2,t} \ge \mathbf{0}
\end{aligned} \quad (5)$$

Note that the standard directional distance functions are originally developed as benefit and shortage functions by Luenberger (1992, 1995), and the name "directional distance function" is used by Chambers, Chung, and Färe (1996).

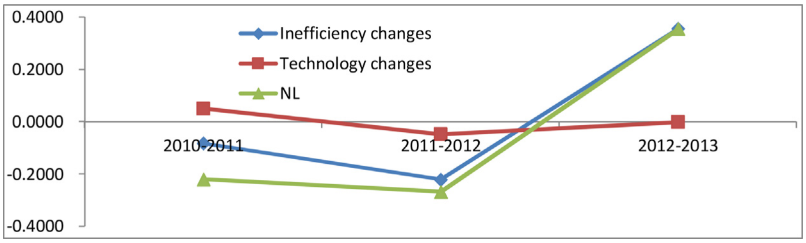

Fig. 5. Changes in the Luenberger productivity indicator and its decompositions over the examined period.

3.2. *Luenberger productivity indicator for productivity changes over time*

We extend our static measures developed in the previous subsection into a Luenberger productivity framework. Multiplicative-form Malmquist productivity indexes were constructed by Caves, Christensen, and Diewert (1982) and Färe, Grosskopf, Lindgren, and Roos (1994), and Chambers (2002) subsequently introduced additive-form Luenberger output productivity indicators. We define a network Luenberger (NL) productivity indicator in a two-stage process setting with lagged carryover variables as

$$NL^{t,t+1}\left(c_o^{t-1},\mathbf{x}_o^{1,t},\mathbf{y}_o^{1,t},x_o^{2,t},y_o^{2,t},c_o^{t},\mathbf{x}_o^{1,t+1},\mathbf{y}_o^{1,t+1},x_o^{2,t+1},y_o^{2,t+1};\mathbf{g}\right)$$

$$=\frac{1}{2}\left[\begin{array}{l}\left\{NDD^{t}\left(c_o^{t-1},\mathbf{x}_o^{1,t},\mathbf{y}_o^{1,t},x_o^{2,t},y_o^{2,t};\mathbf{g}\right)-NDD^{t}\left(c_o^{t},\mathbf{x}_o^{1,t+1},\mathbf{y}_o^{1,t+1},x_o^{2,t+1},y_o^{2,t+1};\mathbf{g}\right)\right\}\\+\left\{NDD^{t+1}\left(c_o^{t-1},\mathbf{x}_o^{1,t},\mathbf{y}_o^{1,t},x_o^{2,t},y_o^{2,t};\mathbf{g}\right)-NDD^{t+1}\left(c_o^{t},\mathbf{x}_o^{1,t+1},\mathbf{y}_o^{1,t+1},x_o^{2,t+1},y_o^{2,t+1};\mathbf{g}\right)\right\}\end{array}\right] \quad (6)$$

where $\mathbf{g}=\left(\mathbf{g}_x^1,\mathbf{g}_y^1,g_x^2,g_y^2\right)$ and constant "1/2" is a coefficient. In Equation (6), we define:

$$NDD^{t}\left(c_o^{t-1},\mathrm{x}_o^{1,t},\mathrm{y}_o^{1,t},x_o^{2,t},x_o^{2,t};\mathrm{g}\right)=\max\quad\beta$$

subject to

$$\begin{array}{llll}c_o^{t-1}\geq\sum_{j=1}^{J}c_j^{t-1}\lambda_j^{1,t}, & \mathrm{x}_o^{1,t}-\beta\mathrm{g}_x^1\geq\sum_{j=1}^{J}\mathrm{x}_j^{1,t}\lambda_j^{1,t}, & \mathrm{y}_o^{1,t}+\beta\mathrm{g}_y^1\leq\sum_{j=1}^{J}\mathrm{y}_j^{1,t}\lambda_j^{1,t}, & \mathrm{z}^{t}\leq\sum_{j=1}^{J}\mathrm{z}_j^{t}\lambda_j^{1,t},\\ \mathrm{z}^{t}\geq\sum_{j=1}^{J}\mathrm{z}_j^{t}\lambda_j^{2,t}, & x_o^{2,t}-\beta g_x^2\geq\sum_{j=1}^{J}x_j^{2,t}\lambda_j^{2,t}, & y_o^{2,t}+\beta g_y^2+c^{t}=\sum_{j=1}^{J}\left(y_j^{2,t}+c_j^{t}\right)\lambda_j^{2,t}, & \\ \mathrm{z}^{t}\geq\mathbf{0}, & c^{t}\geq 0, & \lambda^{1,t}\geq\mathbf{0}, & \lambda^{2,t}\geq\mathbf{0}\end{array} \quad (7a)$$

$$NDD^{t+1}\left(c_o^{t-1},\mathbf{x}_o^{1,t},\mathbf{y}_o^{1,t},x_o^{2,t},y_o^{2,t};\mathbf{g}\right)=\max\quad\beta$$

subject to

$$\begin{array}{llll}c_o^{t-1}\geq\sum_{j=1}^{J}c_j^{t}\lambda_j^{1,t+1}, & \mathbf{x}_o^{1,t}-\beta\mathbf{g}_x^1\geq\sum_{j=1}^{J}\mathbf{x}_j^{1,t+1}\lambda_j^{1,t+1}, & \mathbf{y}_o^{1,t}+\beta\mathbf{g}_y^1\leq\sum_{j=1}^{J}\mathbf{y}_j^{1,t+1}\lambda_j^{1,t+1}, & \mathbf{z}^{t}\leq\sum_{j=1}^{J}\mathbf{z}_j^{t+1}\lambda_j^{1,t+1},\\ \mathbf{z}^{t}\geq\sum_{j=1}^{J}\mathbf{z}_j^{t+1}\lambda_j^{2,t+1}, & x_o^{2,t}-\beta g_x^2\geq\sum_{j=1}^{J}x_j^{2,t+1}\lambda_j^{2,t+1}, & y_o^{2,t}+\beta g_y^2+\mathbf{c}^{t}=\sum_{j=1}^{J}\left(y_j^{2,t+1}+c_j^{t+1}\right)\lambda_j^{2,t+1}, & \\ \mathbf{z}^{t}\geq\mathbf{0}, & c^{t}\geq\mathbf{0}, & \boldsymbol{\lambda}^{1,t+1}\geq\mathbf{0}, & \boldsymbol{\lambda}^{2,t+1}\geq\mathbf{0}\end{array} \quad (7b)$$

$$NDD^{t}\left(c_o^{t},\mathrm{x}_o^{1,t+1},\mathrm{y}_o^{1,t+1},\mathrm{x}_o^{2,t+1},\mathrm{y}_o^{2,t+1};\mathrm{g}\right)=\max\quad\beta$$

subject to

$$\begin{array}{llll}c_o^{t}\geq\sum_{j=1}^{J}c_j^{t-1}\lambda_j^{1,t}, & \mathrm{x}_o^{1,t+1}-\beta\mathrm{g}_x^1\geq\sum_{j=1}^{J}\mathrm{x}_j^{1,t}\lambda_j^{1,t}, & \mathrm{y}_o^{1,t+1}+\beta\mathrm{g}_y^1\leq\sum_{j=1}^{J}\mathrm{y}_j^{1,t}\lambda_j^{1,t}, & \mathrm{z}^{t+1}\leq\sum_{j=1}^{J}\mathrm{z}_j^{t}\lambda_j^{1,t},\\ \mathrm{z}^{t+1}\geq\sum_{j=1}^{J}\mathrm{z}_j^{t}\lambda_j^{2,t}, & x_o^{2,t+1}-\beta g_x^2\geq\sum_{j=1}^{J}x_j^{2,t}\lambda_j^{2,t}, & y_o^{2,t+1}+\beta g_y^2+c^{t+1}=\sum_{j=1}^{J}\left(y_j^{2,t}+c_j^{t}\right)\lambda_j^{2,t}, & \\ \mathrm{z}^{t+1}\geq\mathbf{0}, & c^{t+1}\geq\mathbf{0}, & \lambda^{1,t}\geq 0, & \lambda^{2,t}\geq\mathbf{0}\end{array} \quad (7c)$$

Indicator (6) measures the productivity change for the directional vector **g** for a given production technology formulated by (1) and (2). $NL = NL^{t,t+1}\left(c_o^{t-1}, \mathbf{x}_o^{1,t}, \mathbf{y}_o^{1,t}, x_o^{2,t}, y_o^{2,t}, \mathbf{c}_o^{t}, \mathbf{x}_o^{1,t+1}, \mathbf{y}_o^{1,t+1}, x_o^{2,t+1}, y_o^{2,t+1}; \mathbf{g}\right)$ can be decomposed into inefficiency change (EFFCH) and technological change (TECH) as follows:

$$NL^{t,t+1}(\bullet;\mathbf{g}) = \left\{ \begin{array}{l} \underbrace{NDD^{t}\left(c_o^{t-1}, \mathbf{x}_o^{1,t}, \mathbf{y}_o^{1,t}, x_o^{2,t}, y_o^{2,t}; \mathbf{g}\right) - NDD^{t+1}\left(c_o^{t}, \mathbf{x}_o^{1,t+1}, \mathbf{y}_o^{1,t+1}, x_o^{2,t+1}, y_o^{2,t+1}; \mathbf{g}\right)}_{\text{EFFCH}} \\ \underbrace{+\frac{1}{2}\left[\begin{array}{l} \left\{NDD^{t+1}\left(c_o^{t-1}, \mathbf{x}_o^{1,t}, \mathbf{y}_o^{1,t}, x_o^{2,t}, y_o^{2,t}; \mathbf{g}\right) - NDD^{t}\left(c_o^{t-1}, \mathbf{x}_o^{1,t}, \mathbf{y}_o^{1,t}, x_o^{2,t}, y_o^{2,t}; \mathbf{g}\right)\right\} \\ + \left\{NDD^{t+1}\left(c_o^{t}, \mathbf{x}_o^{1,t+1}, \mathbf{y}_o^{1,t+1}, x_o^{2,t+1}, y_o^{2,t+1}; \mathbf{g}\right) - NDD^{t}\left(c_o^{t}, \mathbf{x}_o^{1,t+1}, \mathbf{y}_o^{1,t+1}, x_o^{2,t+1}, y_o^{2,t+1}; \mathbf{g}\right)\right\} \end{array} \right]}_{\text{TECH}} \end{array} \right\} \quad (8)$$

The values of each indicator, NL, EFFCH or TECH, greater (less) than zero indicate productivity gains (losses).

4. Input and output variables and dataset

Based on the considerations shown in Fig. 1, we selected the variables for Stage 1 and Stage 2.

4.1. Input and output variables

It is important to elaborate on the input and output variables in the efficiency analysis using DEA because these variables can directly and significantly affect the credibility and validity of the analysis. It should be noted that all the monetary variables in this paper have been treated by the Customer Price Index (CPI) to avoid the influence of inflation. The CPI data are shown in Table 1.

In the first stage, we select several inputs, including R&D funds, teaching and research staff, and government block funds. In this stage, the outputs include the number of SCI/SSCI publications, the total number of students (including Ph.D. candidates, master's students, and undergraduates), the total number of patents (including patent applications and authorized patents), and the number of other intellectual property forms (e.g., software copyrights).

(a) R&D funds: This variable refers to the research funding obtained from outside sources (e.g., companies, civil society organizations, foundations). In principle, the funding is allocated by competitive project applications and is used to solve specific scientific and technical problems.
(b) Government block funds: This variable refers to the research funds covering education fees, science expenses, education spending, and the costs of technical equipment updating from the higher authorities by direct allocation. In other words, GBF is a lump-sum amount provided by the central government.
(c) SCI/SSCI publications: Merton (1957, 1968) noted that publication is an important step to establishing the priority of scientific discovery, which is one of scientists' main objectives. Therefore, most research institutions (including universities and research institutes) prefer to assess the performance of its researchers using publication and according citations (Zhang, Banker, Li, & Liu, 2011). Thus, in practice, publication is one of the most important output variables for the measurement of efficiency or scale characteristics of research institutions (see, e.g., Rousseau & Rousseau, 1997; Schubert, 2009; Schmoch & Schubert, 2009; Schubert, 2014; Yang, Rousseau, Yang, & Liu, 2014; Schubert & Yang 2016).
(d) Total number of students: This variable refers to the sum of the numbers of undergraduate, master's students, and Ph.D. candidates taught or trained at the universities each year. Although it may seem that research is one important mission of research universities, focusing on this aspect alone has often overshadowed the other core mission of higher education: teaching and learning. It is necessary to recognize that teaching or training students to provide high-quality human resources for the future is another core and basic output for universities from another point of view. Various measures of teaching or training students have been developed and are used by many existing studies (see, e.g., Avkiran 2001; Glass, McCallion, McKillop, Rasaratnama, & Stringer, 2006; Worthington & Lee, 2008; Schubert, 2014; Schubert & Yang 2016).
(e) Total number of patents: This variable is proxied by the total number of patents, including patent applications and authorized patents. The value of this indicator is calculated as the sum of patent applications and authorized patents by the State Intellectual Property Office. It should be noted that patent applications can also be sold according to the current regulations in China.
(f) Number of other intellectual properties: This variable refers to intellectual properties whose designer is assigned a monopoly by law, except the patents, e.g., software copyright and industrial design rights.

In the second stage, in addition to the two inputs (number of patents, number of other intellectual properties) that are the outputs of the first stage, there is an extra input reflecting the staff of the application of R&D outputs and technology

Table 1
The CPI data in China over the period 2009–2013.

Year	CPI value
2009	96.783
2010	100.000
2011	105.471
2012	108.222
2013	111.070

Note: This CPI data are from OECD (2010) and index 2010 = 100.

services in this stage. The single output of the second stage is TI, which is the sum of TT revenue and the income from selling patents.

(g) Staff of application of R&D outputs and technology services: This variable refers to the personnel engaged in the work of transforming new products, materials, and devices generated from the R&D stage to practical production. In other words, it refers to the number of staff working in R&D and technology services.
(h) Total income (TI): TI refers to the sum of TT revenue and income from selling patents, which can be obtained separately from the data source mentioned in Section 4.2. Technology transfer is a process through which technical information and products developed by the university are provided to potential users to encourage and accelerate their evaluation and/or use. TT revenue refers to the revenue of R&D outputs and technology services at the universities. The income from selling patents denotes the income of authorized patents sold by the university in a given statistical year.

4.2. Data source

First, we consider all the universities that are directly managed by the Ministry of Education of China. Second, we remove several special categories of universities, including art universities, finance universities, and language universities (e.g., Central Conservatory of Music and China Central Academy of Fine Arts) because they do not aim to produce scientific publications and technology transfer. Consequently, we have 64 universities in our sample to investigate. All 64 sample universities are Project 211 universities,[2] which can be considered representative of high-standard Chinese research universities. The input and output variables are collected from the Statistical Yearbooks 2010–2014 issued by the Ministry of Education of China, except the SCI/SSCI publications, which were obtained from the Incites database[3] and were provided by Thomson Reuters on August 15, 2015.

4.3. Descriptive statistics

Table A1 in Appendix A shows the descriptive statistics of input and output variables. We can see the changes of the average of variables in Fig. 2. From this figure, we can determine that almost all indicators grow in the examined period, except staff from the application of R&D outputs and technology services. For instance, the average value of R&D funds increased from 541,430.97 in 2009–817,651.69 in 2013. The average value of government block funds increased from 306,256.52 in 2009–486,110.73 in 2013. However, the average staff from the application of R&D outputs and technology services dropped over this period from 198.95 to 168.98. See Fig. 2 for details.

5. Empirical results and policy implications

5.1. Inefficiency analysis of four separate years

We set the coefficient $\alpha = 50\%$ as the proportion of the TI (Total income) in Fig. 1. Thus, based on model (5), we have the following results for NDD in different years for 64 Chinese research universities. See Table A2 in Appendix A.

Fig. 3 shows the truncated kernel density graphs of the value of the NDD measure of the four separate years. We can see the distribution of the NDD values. In this figure, we find that most DMUs in 2010, 2011, and 2013 are distributed with NDD values in the interval [0,0.6], which means the overall efficiency level of those universities is relatively high (a NDD value represents inefficiency, i.e., the higher the NDD value is, the more inefficient it is). However, in 2012, there were more universities with NND values that became larger than 0.6, which indicates deteriorated overall efficiency in this year. In 2013, the overall efficiency improved, and most of the NDD values are again distributed in the interval [0,0.6].

[2] Project 211 is a project of National Key Universities and Colleges, initiated in 1995 by the Ministry of Education (MoE) of China, with the intent to raise the research standards of high-level universities and cultivating strategies for socio-economic development (Li 2004). Today, China has 116 universities of higher education designated as Project 211 institutions for having met certain scientific, technical, and human resource standards and offer advanced degree programmes. Project 211 universities in China are responsible for training about four-fifths of doctoral students, two-thirds of graduate students, half of students from abroad and one-third of undergraduates.

[3] http://incites.isiknowledge.com/Home.action.

Table 2
Top 5 universities contributing to efficiency improvement and technology changes.

Periods	Efficiency changes		Technological changes	
	From 2010–2011 to 2011–2012	From 2011–2012 to 2012–2013	From 2010–2011 to 2011–2012	From 2011–2012 to 2012–2013
Top 5 universities	DMU_1	DMU_{28}	DMU_{57}	DMU_{56}
	DMU_{62}	DMU_{63}	DMU_{64}	DMU_{16}
	DMU_{27}	DMU_{20}	DMU_{37}	DMU_{57}
	DMU_{22}	DMU_{46}	DMU_{15}	DMU_{64}
	DMU_{34}	DMU_1	DMU_{56}	DMU_{35}

The average value of the NDD measure in the four separate years shows an inverted U-shape, which means that the average inefficiency level of the 64 Chinese research universities continuously increases from 2010 to 2012; next, in 2013, the inefficiency level dropped significantly. See Fig. 4 for the trend; see also the last row of Table A2 in Appendix A.

5.2. *Productivity gain over time: a productivity indicator*

We next investigate the productivity gain over time for these 64 research universities in China. Fig. 5 shows the changes of the network Luenberger productivity indicator (NL) and its decompositions over the examined period. We can see that NL dropped significantly from 2010–2011 to 2011–2012. However, NL increased significantly in the next period (from the period 2011–2012 to the period 2012–2013) and reached 0.375. The changes in NL are mainly driven by inefficiency changes, which change with similar patterns of NL for the entire examined period. See details in the last row of Table A3 in Appendix A.

Along with an improvement of NDD from 2012 to 2013, the significantly improved NL value from 2011-2012 to 2012-2013 is an indication that “The Plan” (See Section 5.5) had a positive effect on the productivity improvement. However, the technology suffered from deterioration in 2011–2012 and 2012–2013 with negative NL values, which means that there was a technological regression during the periods.[4] This somewhat surprising evidence has an important policy implication; hence, we discuss it in the next subsection.

Table 2 shows the top five universities that contributed to efficiency changes and technological changes in each period. From 2010–2011 to 2011–2012, the average efficiency of those universities deteriorated, and the top five universities contributing to these changes include DMU_1, DMU_{62}, DMU_{27}, DMU_{22}, and DMU_{34}. Similarly, we can see that DMU_{28}, DMU_{63}, DMU_{20}, DMU_{46}, and DMU_1 are the top five universities that contributed to the efficiency improvement from 2011 to 2012 to 2012–2013.

The pattern of technology changes is similar to that of efficiency changes in the examined period. From 2010–2011 to 2011–2012, there was a decline in terms of the average technological change indicator. However, there was a technological improvement in the next period from 2011–2012 to 2012–2013. In the shift from 2010–2011 to 2011–2012, DMU_{57}, DMU_{64}, DMU_{37}, DMU_{15}, and DMU_{56} ranked as the top five universities that contributed to the technological decline. From 2011–2012 to 2012–2013, DMU_{56}, DMU_{16}, DMU_{57}, DMU_{64}, and DMU_{35}, which were the top five universities, contributed the technological improvement.

5.3. *Heterogeneity of project 985 and non-project 985 universities*

Project 985, which was proposed in 1998 by the Chinese government, is a programme in which the Chinese government aims to create world-class and high-level universities.[5] The MoE of China stated that the Chinese government would devote one percent of its fiscal revenue each year to building world-class universities. Currently, there are 38 Project 985 universities. Yang, Yang, Xu, and Khoveyni (2017) assessed the performance of the 38 Project 985 universities. Interested readers can refer to Yang et al. (2017) for details. See also Zhang, Patton, and Kenney (2013). All 64 universities in our sample are directly managed by the MoE. Among these universities, there are 31 Project 985 universities and 33 non-Project 985 universities. Detailed information is shown in Table 3.

We first investigate the inefficiencies (i.e., NDD values) of four separate years for Project 985 and non-Project 985 universities. We find that the Project 985 universities (leading universities) perform better than the non-Project 985 ones in terms of NDD values. Furthermore, the inefficiency gap between these two groups became larger except in 2012–2013, in which the difference narrowed slightly. See Fig. 6 for details.

We further investigate the heterogeneity of the network Luenberger productivity indicator and its decomposed productivity components with respect to Project 985 and non-Project 985 universities. We observe the following: (1) NL and

[4] Note: The possible reason may be twofold: (1) there is a lack of a performance-based budget management system to improve the universities' efficiency; (2) there is too much resources input into the universities, and there may be a time lag for the corresponding outcomes.

[5] https://www.sicas.cn/Students/Info/Content_110720132652705.shtml Note that the original list of the project included the National University of Defense Technology, but we removed this university from our analysis because it does not provide data.

Table 3
Project 985 and non-Project 985 universities.

No.	Project 985 universities	Non-Project 985 universities
1	DMU_1	DMU_4
2	DMU_2	DMU_5
3	DMU_3	DMU_6
4	DMU_8	DMU_7
5	DMU_{11}	DMU_9
6	DMU_{18}	DMU_{10}
7	DMU_{19}	DMU_{12}
8	DMU_{20}	DMU_{13}
9	DMU_{21}	DMU_{14}
10	DMU_{22}	DMU_{15}
11	DMU_{25}	DMU_{16}
12	DMU_{26}	DMU_{17}
13	DMU_{27}	DMU_{23}
14	DMU_{30}	DMU_{24}
15	DMU_{31}	DMU_{28}
16	DMU_{32}	DMU_{29}
17	DMU_{38}	DMU_{33}
18	DMU_{40}	DMU_{34}
19	DMU_{41}	DMU_{35}
20	DMU_{42}	DMU_{36}
21	DMU_{44}	DMU_{37}
22	DMU_{45}	DMU_{39}
23	DMU_{50}	DMU_{43}
24	DMU_{51}	DMU_{46}
25	DMU_{52}	DMU_{47}
26	DMU_{54}	DMU_{48}
27	DMU_{56}	DMU_{49}
28	DMU_{58}	DMU_{53}
29	DMU_{59}	DMU_{55}
30	DMU_{62}	DMU_{57}
31	DMU_{64}	DMU_{60}
32		DMU_{61}
33		DMU_{63}

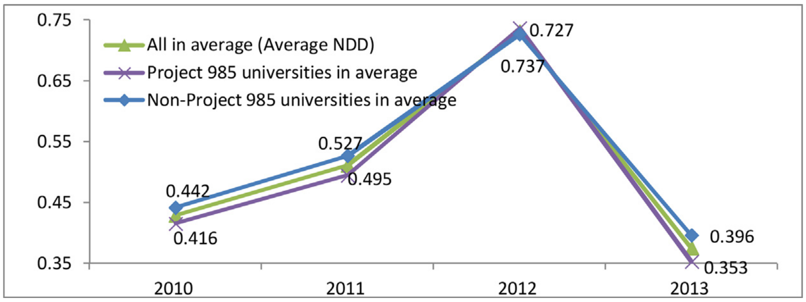

Fig. 6. NDD values of Project 985 and non-Project 985 universities.

technology changes of these two groups of universities show a similar trend of evolution, (2) in 2012–2013, the technology change of non-Project 985 universities is positive and shows improvement. However, technology changes of Project 985 universities are negative in 2011–2012 and 2012–2013, which continuously deteriorate over the examined period, (3) Project 985 universities perform worse than non-Project 985 universities with respect to the inefficiency changes in 2011–2012. However, in 2012–2013, Project 985 universities perform considerably better than non-Project 985 universities. This evidence shows that Project 985 universities improved their efficiency much more quickly than non-Project 985 universities over the examined period. See Fig. 7.

5.4. Sensitivity analysis

In this subsection, we first compare the NDDs using our dynamic network DEA and black-box directional distances (BDDs) of each university in different years. See Appendix B for details on how to calculate BDD using DEA model by treating DMUs as a “black box”. Table 4 shows the Pearson correlations between NDDs and BDDs in each year over the examined period.

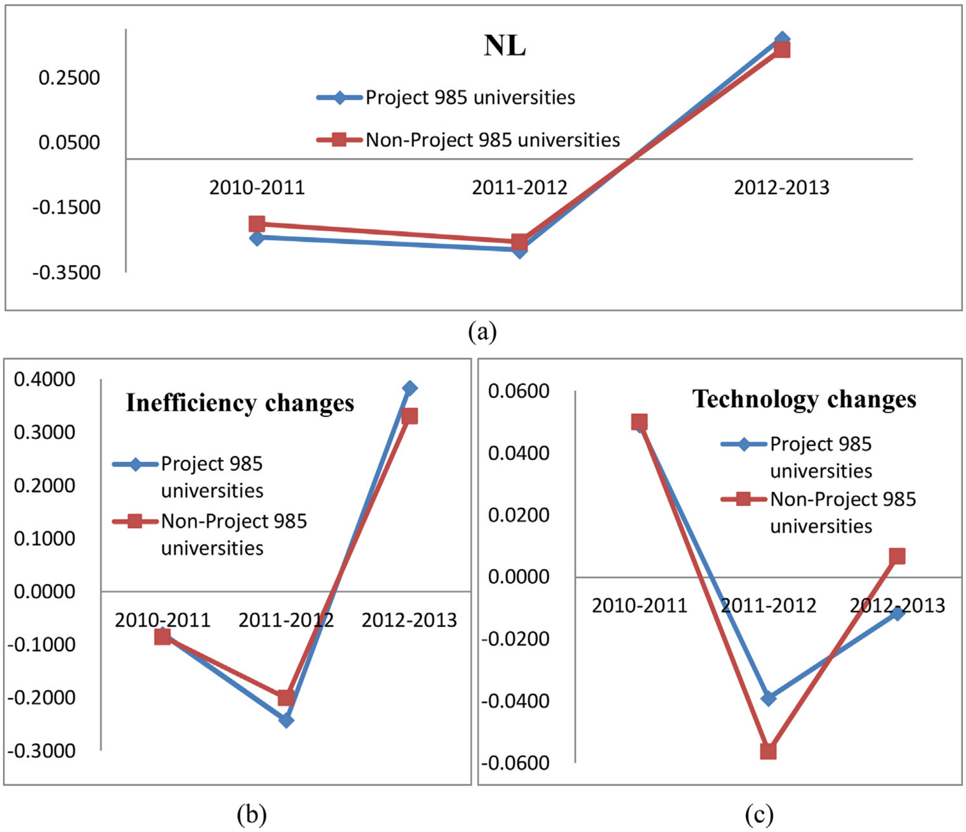

Fig. 7. Luenberger productivity indicator and its decompositions.

Table 4
Pearson correlation coefficients.

	2010	2011	2012	2013
2010	0.860			
2011		0.788		
2012			0.515	
2013				0.950

Table 5
Results of the sensitivity analysis on coefficient α.

	Average NDD			
Coefficient α	2010	2011	2012	2013
0.1	0.434	0.747	0.401	0.377
0.2	0.434	0.515	0.738	0.377
0.3	0.434	0.514	0.736	0.376
0.4	0.433	0.513	0.734	0.376
0.5	0.429	0.511	0.732	0.375
0.6	0.425	0.510	0.729	0.375
0.7	0.420	0.508	0.727	0.374
0.8	0.415	0.507	0.724	0.374
0.9	0.411	0.505	0.721	0.373

In Table 4, we find that there is a significant difference between NDDs and BDDs. In particular, in 2012, the Pearson correlation coefficient is only 0.515. This fact means that our dynamic network DEA can open the "black box" and go inside the DMUs to consider the loops over different years and the connections between two sub-stages.

Second, we also investigate the NDDs of each university with a different coefficient α. We find that the average NDDs intend to decrease with the growth of coefficient α. See details in Table 5.

5.5. Policy implications and suggestions

At the end of 2013, there were 2491 general universities in China, 113 of which were directly affiliated with the ministries and commissions, 75 of which were directly affiliated with the Ministry of Education, and 830 of which were postgraduate training institutions. The total number of college and university students was 34.6 million, 24.681 million of whom were undergraduate students, 1.794 million were graduate students, and 6.2641 million were college students.

In recent years, Chinese higher education has developed significantly. First, the proportion of financial investment in higher education in China's total GDP reached 0.87% in 2011, and the country's total investment in education accounted for 4% of GDP, not including such funding sources as special funds and research and investment funds. Second, by the end of 2013, the total number of staff members in China's higher education system was 2,296,300, of whom 1,496,900 were full-time teachers, according to the official statistics published by MoE. From 2007–2011, the cumulative number of granted master degrees and doctorate degrees reached 580,000 and 1 million, respectively. China's annual number of doctoral degrees has reached the top spot globally, and the proportion of the national population that completed higher education increased from 6.2% in 2007–8.9% in 2010. Third, Chinese universities have undertaken more than 60% of national major scientific research projects and more than 80% of those from the National Natural Science Foundation (NSFC).

Fourth, in 2011, seven, three and one Chinese universities were listed in the top 200 universities in the world rankings of "QS" World University Rankings, "Times Higher Education Special Issue" (UK), and Academic Ranking of China Shanghai Jiaotong University, respectively. This performance plays a leading role in developing countries, and the gap between China and some developed countries are narrowing; for example, Japan and France had 11, 5, and 9 and 4, 5, and 8 universities listed in the above world rankings, respectively. Fifth, the number of published papers in China has also been increasing. In 2011, Chinese research institutions published the largest number of papers in engineering indexed journals. The number of published papers in the indexed journals of the natural sciences ranked second only to the United States. In contrast, the level of research in the field of social sciences in China needs to be further improved.

The abovementioned development and improvement in Chinese higher education is closely related to the implementation and effect of China's higher education policy. However, China's higher education system still faces opportunities and major challenges. For this reason, China's higher education policy and reform should continue in a sustainable way with consideration of both efficiency and quality.

Given the background information mentioned above, it is necessary to study the National Long-term Education Reform and Development Plan (2010–2020), which we shortened to "The Plan" inection 5.2, that was issued by the central government in May 2012. An important background aspect is that China's higher education has been changing from elite education to mass education. "The Plan" states that it is necessary to improve the quality of higher education in China. By 2020, the structure of higher education in China must be more rational, and a higher education system with international standards should be built. To this end, "The Plan" requires Chinese research universities to improve the quality of student training. The government should increase investments in teaching, continuously improve the level of education and teaching, and deepen the reform of teaching. "The Plan" also calls for Chinese universities to improve the level of scientific research and strengthen basic research. Furthermore, Chinese universities should not only strengthen their social service capabilities and promote the combination of production, learning and research but also should accelerate the transformation of scientific and technological achievements to improve the public's scientific and humanistic knowledge.

The second important education policy required by "The Plan" is to accelerate the reform of institutional mechanisms in colleges and universities and change the methods of teaching and research in colleges and universities.

Based on the empirical findings of large resource misallocations, slow technological improvement and technological regression, as well as differences in performance between the two types of universities, we propose the following policy suggestions: (i) It is necessary to introduce a performance-based budget management system, which links government funding to some selected performance indicators, such as our network Luenberger productivity indicator. (ii) Universities need to pay much more attention to technology transfer to boost research outcomes to serve the development of the economy and society through reasonable financial allocation to technology transfer activities. (iii) The government should give special attention to non-Project 985 universities (e.g., non-leading universities) to improve their output capacity and performance based on the current input of limited resources, e.g., non-Project 985 universities can fully implement the tenure track system for staff; most Project 985 universities have done this so that the staff can be better motivated and have more mobility to benefit their capacity improvement and improve the inefficiency status of non-Project 985 universities.

Regarding suggestion (ii), the technology of the sample research universities did not show technological advancement; in fact, the technological deterioration was signified by a negative value of the technological change indicator that occurred over the last two sample periods (see the previous Section 5.3). It may be reasonable to suggest a policy of attracting more talent from other countries in view of the present development status of Chinese higher education. China is still at an early stage of development with respect to teaching, innovation and advancement of technology. Although the Chinese government has made an effort to attract qualified overseas talent in recent years, it is possible to further strengthen the intensity to invite more qualified overseas talent, particularly qualified university professors of Chinese origin from the US and Europe (professors of Chinese origin can easily adjust to life in China), not only to enhance the quality of teaching but also to improve the research output through government initiatives. In the meantime, the Chinese government also needs to increase the training of local talent to achieve international first-class standards.

Regarding policy suggestion (iii), the tenure track system can implement academic research performance as an important criterion, i.e., faculty members are required to conduct research in addition to teaching. If the Chinese government emphasizes the importance of research to non-Project 985 universities as well, its implementation will offer them the following possible advantages: (1) It can significantly help professors progress and achieve their greatest potential; (2) It can give qualified professors more freedom to work on difficult academic issues and make breakthroughs. Chang et al. (2012) emphasized the importance of research activities for the tourism and leisure departments at Taiwanese universities to develop the professional capabilities of teachers and professors. While this finding is confined to the special case of tourism and leisure departments of universities, it may provide some justification of advancing research activities in Chinese higher education. Currently, the tenure track system is implemented in most Project 985 universities and has seen good results. The government should extend the tenure track system in non-Project 985 universities to further enhance their innovation potential.

The US National Science Foundation[6] states that what is "considered interdisciplinary today might be considered disciplinary tomorrow". Taking this view into account, we propose that Chinese research universities fully consider the interdisciplinary research of colleges and universities from a forward-looking scientific perspective. We believe that interdisciplinary research by teams or individuals who integrate concepts and theories from two or more disciplines will be further effective in producing more scientific breakthroughs and training more qualified students. Since the recent adoption of the interdisciplinary research concept through international cooperation has had a positive impact on Chinese higher education, its continued efforts appear to help Chinese universities meet the government's goal of building world-class universities in such a way that international standards are implemented.

6. Discussions and conclusions

In this paper, we first developed a network directional distance framework based on a two-stage network DEA model to gauge the inefficiencies of Chinese research universities directly managed by the MoE, which is the department in charge of the country's education. Second, we also proposed a network Luenberger productivity indicator to measure productivity evolution over time, as well as its decompositions. The empirical results show that the average efficiencies of our 64 sample universities increased within the examined period of 2010–2013. However, the technology changes were negative in the latter periods, which illustrates that the technology suffered a decline for those universities in this period. Furthermore, the inefficiency changes of Project 985 universities were much better than those of non-Project 985 universities. We also offer the following consideration: As we discussed in Section 2.2, in the second stage, coefficient α represents the proportion of the patent income consisting of TT revenue and income from the sale of patents. We conducted the sensitivity analysis of our results, including the comparison of NDDs and BDDs and using different values of α. It should be noted that the value of α is determined by policy makers of the central government. In this paper, we set it equal to 50% according to the existing regulations. Finally, we proposed several policy suggestions for the sustainable development of Chinese research universities. In future research, we can further investigate the efficiency and productivity evolution when the proportions are different and less than 50% as new policy thresholds interact with new regulations in the technology transfer activities of Chinese universities from the central government.

Author contributions

Guo-liang Yang: Conceived and designed the analysis, Collected the data, Contributed data or analysis tools, Performed the analysis, Wrote the paper.

Hirofumi Fukuyama: Conceived and designed the analysis, Collected the data, Contributed data or analysis tools, Performed the analysis, Wrote the paper.

Yao-yao Song: Conceived and designed the analysis, Collected the data, Contributed data or analysis tools, Performed the analysis, Wrote the paper.

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Appendix A.

[6] https://www.nsf.gov/od/oia/additional_resources/interdisciplinary_research/definition.jsp.

[7] FTE denotes the full-time equivalence.

Table A1
Descriptive statistics on input and output variables.

Year	Statistics	Input and output variables							
		RDF (unit: thousand RMB)	GBF (unit: thousand RMB)	SCI/SSCI PUB. (unit: number)	TNS (unit: number)	TNP (unit: number)	OIP (unit: number)	SARDOTS (unit: FTE[7])	TI (unit: thousand RMB)
2009	Min	5685.89	4342.69	12.00	2010.00	2.00	0.00	0.00	0.00
	Max	2290112.77	1438534.91	4824.00	16720.00	3052.00	165.00	1368.00	370698.00
	Median	428913.95	216827.99	684.00	7122.00	328.00	0.00	114.50	4212.00
	Mean	541430.97	306256.52	1082.41	7855.98	434.72	14.78	198.95	22683.83
	Standard deviation	462282.08	292123.78	1047.26	3223.80	510.79	32.31	279.38	55773.55
2010	Min	10527.00	5813.00	24.00	2819.00	6.00	0.00	0.00	0.00
	Max	2612051.00	1561000.00	4977.00	34570.00	3445.00	334.00	873.00	531038.00
	Median	459555.50	239318.50	777.00	7701.50	429.50	6.00	102.50	5895.00
	Mean	576053.31	319957.45	1188.72	8717.41	550.22	28.00	155.05	28215.14
	Standard deviation	491612.05	306593.61	1103.58	4624.08	619.69	58.65	186.81	71933.95
2011	Min	10374.46	8553.09	21.00	2183.00	8.00	0.00	0.00	0.00
	Max	3445268.16	2293000.13	5723.00	17715.00	4266.00	211.00	979.00	673849.00
	Median	575394.94	318114.72	895.00	7776.00	530.50	9.00	116.50	5100.00
	Mean	741517.94	468823.33	1397.30	8353.91	710.55	30.30	160.31	32309.11
	Standard deviation	659251.42	495685.74	1272.99	3368.33	821.83	49.98	185.62	88552.36
2012	Min	8467.77	6965.31	20.00	2461.00	6.00	0.00	0.00	0.00
	Max	3595552.11	2365003.08	6406.00	17875.00	4798.00	240.00	854.00	749347.00
	Median	539111.24	321197.33	1027.50	7985.50	669.50	7.50	86.50	6150.00
	Mean	755069.70	453399.44	1614.58	8552.36	882.44	24.81	145.95	35937.67
	Standard deviation	670294.01	474915.14	1457.73	3297.08	1012.39	42.63	167.80	100653.43
2013	Min	14013.65	6440.07	22.00	2525.00	0.00	0.00	0.00	0.00
	Max	3917371.25	2713444.55	7354.00	17955.00	5138.00	385.00	1583.00	806801.00
	Median	605579.98	326466.66	1200.50	8153.50	890.50	21.50	86.50	7261.00
	Mean	817651.69	486110.73	1888.81	8761.61	1155.50	50.92	168.98	41473.67
	Standard deviation	725829.44	504163.38	1688.30	3290.79	1075.81	72.13	240.14	111650.99

Table A2
NDD in different years and corresponding rankings.

DMUs	2010		2011		2012		2013	
	Value	Ranking	Value	Ranking	Value	Ranking	Value	Ranking
DMU_1	0.597	17	0.873	1	0.904	2	0.722	1
DMU_2	0.000	60	0.000	61	0.000	63	0.000	62
DMU_3	0.538	22	0.664	18	0.811	21	0.603	6
DMU_4	0.691	7	0.722	11	0.875	6	0.523	16
DMU_5	0.773	1	0.713	14	0.892	3	0.534	15
DMU_6	0.460	33	0.559	29	0.712	43	0.419	27
DMU_7	0.487	29	0.703	16	0.747	37	0.431	24
DMU_8	0.656	12	0.787	5	0.846	12	0.552	13
DMU_9	0.714	5	0.749	10	0.758	34	0.320	41
DMU_{10}	0.000	60	0.421	45	0.619	57	0.213	55
DMU_{11}	0.164	55	0.356	54	0.699	46	0.140	58
DMU_{12}	0.082	57	0.241	57	0.426	62	0.344	35
DMU_{13}	0.000	60	0.000	61	0.000	63	0.000	62
DMU_{14}	0.180	54	0.369	52	0.695	47	0.328	38
DMU_{15}	0.703	6	0.828	2	0.910	1	0.579	8
DMU_{16}	0.671	11	0.806	3	0.867	7	0.647	3
DMU_{17}	0.688	8	0.757	9	0.877	5	0.491	17
DMU_{18}	0.290	49	0.427	44	0.595	58	0.116	60
DMU_{19}	0.536	23	0.571	25	0.829	17	0.407	29
DMU_{20}	0.318	46	0.351	55	0.689	49	0.323	40
DMU_{21}	0.385	41	0.403	47	0.806	24	0.591	7
DMU_{22}	0.349	43	0.466	41	0.781	30	0.367	31
DMU_{23}	0.104	56	0.000	61	0.592	59	0.076	61
DMU_{24}	0.496	27	0.372	50	0.674	52	0.215	54
DMU_{25}	0.293	48	0.559	28	0.792	26	0.369	30
DMU_{26}	0.607	16	0.597	24	0.840	14	0.577	10
DMU_{27}	0.481	31	0.551	32	0.788	28	0.430	25
DMU_{28}	0.457	34	0.387	48	0.705	44	0.319	42
DMU_{29}	0.198	53	0.145	59	0.624	56	0.230	52
DMU_{30}	0.454	35	0.452	42	0.755	35	0.293	45
DMU_{31}	0.298	47	0.405	46	0.693	48	0.275	48
DMU_{32}	0.528	25	0.515	36	0.772	31	0.325	39
DMU_{33}	0.433	37	0.524	33	0.749	36	0.276	47
DMU_{34}	0.672	10	0.720	12	0.854	9	0.476	19
DMU_{35}	0.260	51	0.236	58	0.704	45	0.346	33
DMU_{36}	0.736	4	0.766	8	0.781	29	0.476	20
DMU_{37}	0.000	60	0.710	15	0.636	54	0.316	43
DMU_{38}	0.540	21	0.600	23	0.817	19	0.466	22
DMU_{39}	0.519	26	0.517	35	0.722	42	0.365	32
DMU_{40}	0.339	45	0.370	51	0.743	38	0.330	37
DMU_{41}	0.248	52	0.256	56	0.740	39	0.259	51
DMU_{42}	0.483	30	0.568	26	0.808	23	0.579	9
DMU_{43}	0.678	9	0.770	7	0.817	20	0.617	4
DMU_{44}	0.487	28	0.556	31	0.759	33	0.344	34
DMU_{45}	0.529	24	0.617	21	0.833	15	0.467	21
DMU_{46}	0.580	19	0.681	17	0.888	4	0.554	12
DMU_{47}	0.343	44	0.495	39	0.790	27	0.550	14
DMU_{48}	0.752	3	0.777	6	0.847	11	0.605	5
DMU_{49}	0.024	59	0.366	53	0.668	53	0.139	59
DMU_{50}	0.637	15	0.618	20	0.841	13	0.411	28
DMU_{51}	0.564	20	0.474	40	0.771	32	0.307	44
DMU_{52}	0.391	40	0.513	37	0.738	40	0.171	57
DMU_{53}	0.589	18	0.556	30	0.833	16	0.564	11
DMU_{54}	0.473	32	0.505	38	0.683	50	0.184	56
DMU_{55}	0.440	36	0.449	43	0.674	51	0.273	49
DMU_{56}	0.266	50	0.380	49	0.635	55	0.265	50
DMU_{57}	0.410	38	0.612	22	0.808	22	0.425	26
DMU_{58}	0.378	42	0.560	27	0.730	41	0.341	36
DMU_{59}	0.403	39	0.521	34	0.794	25	0.289	46
DMU_{60}	0.652	13	0.641	19	0.826	18	0.477	18
DMU_{61}	0.759	2	0.792	4	0.862	8	0.709	2
DMU_{62}	0.651	14	0.717	13	0.851	10	0.445	23
DMU_{63}	0.038	58	0.000	61	0.548	60	0.229	53
DMU_{64}	0.000	60	0.107	60	0.499	61	0.000	62
AVERAGE	0.429		0.511		0.732		0.375	

Table A3
Changes in Luenberger productivity indicator and its decompositions over time.

DMUs	2010–2011			2011–2012			2012–2013		
	EFFCH	TECH	NL	EFFCH	TECH	NL	EFFCH	TECH	NL
DMU_1	−0.276	0.185	−0.031	−0.031	−0.054	−0.086	0.181	−0.010	0.172
DMU_2	0.000	−0.091	0.000	0.000	−0.431	−0.431	0.000	0.601	0.601
DMU_3	−0.126	0.035	−0.147	−0.147	0.007	−0.139	0.209	−0.032	0.177
DMU_4	−0.031	0.014	−0.152	−0.152	−0.034	−0.186	0.352	−0.083	0.269
DMU_5	0.060	−0.060	−0.179	−0.179	0.009	−0.170	0.358	−0.108	0.251
DMU_6	−0.099	0.118	−0.153	−0.153	−0.123	−0.276	0.293	0.072	0.365
DMU_7	−0.216	0.184	−0.044	−0.044	−0.206	−0.250	0.316	0.055	0.370
DMU_8	−0.132	0.075	−0.059	−0.059	−0.096	−0.155	0.294	0.003	0.298
DMU_9	−0.035	−0.017	−0.008	−0.008	−0.199	−0.207	0.437	−0.004	0.434
DMU_{10}	−0.421	0.342	−0.198	−0.198	−0.141	−0.339	0.406	0.112	0.518
DMU_{11}	−0.191	0.108	−0.343	−0.343	0.011	−0.332	0.558	−0.072	0.487
DMU_{12}	−0.159	0.196	−0.185	−0.185	0.043	−0.142	0.082	0.071	0.153
DMU_{13}	0.000	0.081	0.000	0.000	−0.157	−0.157	0.000	0.091	0.091
DMU_{14}	−0.188	0.138	−0.326	−0.326	−0.044	−0.370	0.367	0.074	0.441
DMU_{15}	−0.125	0.122	−0.082	−0.082	−0.048	−0.131	0.331	−0.096	0.235
DMU_{16}	−0.134	0.126	−0.062	−0.062	−0.093	−0.155	0.220	0.013	0.233
DMU_{17}	−0.069	0.046	−0.121	−0.121	−0.058	−0.179	0.386	−0.104	0.282
DMU_{18}	−0.137	−0.095	−0.168	−0.168	−0.042	−0.210	0.479	−0.075	0.404
DMU_{19}	−0.035	0.005	−0.258	−0.258	0.005	−0.253	0.422	−0.104	0.318
DMU_{20}	−0.033	0.050	−0.338	−0.338	−0.022	−0.360	0.366	0.044	0.410
DMU_{21}	−0.019	0.010	−0.403	−0.403	0.108	−0.295	0.215	0.073	0.288
DMU_{22}	−0.116	0.091	−0.315	−0.315	0.007	−0.308	0.414	−0.041	0.373
DMU_{23}	0.104	−0.124	−0.592	−0.592	0.143	−0.449	0.516	0.038	0.554
DMU_{24}	0.124	−0.136	−0.302	−0.302	−0.054	−0.356	0.459	0.001	0.460
DMU_{25}	−0.266	0.242	−0.232	−0.232	−0.009	−0.241	0.423	−0.037	0.386
DMU_{26}	0.010	−0.005	−0.243	−0.243	0.005	−0.238	0.263	0.004	0.267
DMU_{27}	−0.070	0.063	−0.237	−0.237	−0.037	−0.274	0.357	0.008	0.366
DMU_{28}	0.070	−0.051	−0.318	−0.318	0.010	−0.309	0.387	−0.031	0.355
DMU_{29}	0.053	−0.051	−0.480	−0.480	0.060	−0.421	0.395	0.070	0.465
DMU_{30}	0.002	−0.054	−0.303	−0.303	0.019	−0.285	0.462	−0.034	0.428
DMU_{31}	−0.107	0.096	−0.288	−0.288	−0.061	−0.349	0.418	0.001	0.419
DMU_{32}	0.013	0.003	−0.257	−0.257	0.013	−0.244	0.447	−0.125	0.322
DMU_{33}	−0.091	0.106	−0.225	−0.225	−0.053	−0.277	0.473	−0.064	0.409
DMU_{34}	−0.048	0.047	−0.134	−0.134	−0.062	−0.196	0.378	−0.076	0.302
DMU_{35}	0.024	−0.023	−0.468	−0.468	0.090	−0.378	0.358	0.049	0.407
DMU_{36}	−0.030	−0.004	−0.015	−0.015	−0.180	−0.195	0.305	0.063	0.368
DMU_{37}	−0.710	0.713	0.074	0.074	−0.363	−0.289	0.320	0.147	0.467
DMU_{38}	−0.060	0.067	−0.217	−0.217	−0.026	−0.244	0.351	−0.036	0.315
DMU_{39}	0.001	−0.751	−0.205	−0.205	−0.042	−0.247	0.357	−0.344	0.013
DMU_{40}	−0.030	0.039	−0.373	−0.373	0.023	−0.350	0.413	0.009	0.423
DMU_{41}	−0.008	0.032	−0.484	−0.484	0.115	−0.369	0.481	−0.044	0.437
DMU_{42}	−0.085	0.044	−0.240	−0.240	−0.030	−0.270	0.229	0.071	0.299
DMU_{43}	−0.093	0.086	−0.046	−0.046	−0.131	−0.177	0.200	0.072	0.271
DMU_{44}	−0.069	0.068	−0.203	−0.203	−0.093	−0.296	0.415	−0.037	0.379
DMU_{45}	−0.088	0.070	−0.216	−0.216	−0.020	−0.236	0.366	−0.052	0.314
DMU_{46}	−0.101	0.053	−0.207	−0.207	0.012	−0.194	0.334	−0.071	0.263
DMU_{47}	−0.152	0.145	−0.295	−0.295	0.011	−0.284	0.240	0.071	0.311
DMU_{48}	−0.024	0.012	−0.071	−0.071	−0.092	−0.163	0.242	0.046	0.287
DMU_{49}	−0.342	0.253	−0.302	−0.302	−0.054	−0.356	0.528	0.007	0.536
DMU_{50}	0.019	−0.019	−0.223	−0.223	0.001	−0.223	0.430	−0.110	0.320
DMU_{51}	0.090	−0.093	−0.297	−0.297	−0.006	−0.303	0.464	−0.074	0.390
DMU_{52}	−0.122	0.071	−0.225	−0.225	−0.070	−0.295	0.567	−0.104	0.462
DMU_{53}	0.033	−0.022	−0.276	−0.276	0.029	−0.247	0.268	0.008	0.276
DMU_{54}	−0.032	0.032	−0.178	−0.178	−0.147	−0.325	0.500	−0.047	0.453
DMU_{55}	−0.008	−0.010	−0.226	−0.226	−0.069	−0.294	0.401	0.024	0.425
DMU_{56}	−0.114	0.130	−0.255	−0.255	−0.120	−0.375	0.370	0.066	0.436
DMU_{57}	−0.202	0.157	−0.196	−0.196	−0.043	−0.239	0.383	−0.040	0.344
DMU_{58}	−0.183	0.140	−0.169	−0.169	−0.126	−0.296	0.389	−0.028	0.361
DMU_{59}	−0.118	0.130	−0.273	−0.273	0.000	−0.273	0.505	−0.126	0.380
DMU_{60}	0.011	−0.015	−0.185	−0.185	−0.056	−0.241	0.349	−0.036	0.313
DMU_{61}	−0.033	0.071	−0.070	−0.070	−0.028	−0.098	0.153	−0.014	0.139
DMU_{62}	−0.066	0.032	−0.134	−0.134	−0.043	−0.177	0.406	−0.074	0.332
DMU_{63}	0.038	−0.091	−0.548	−0.548	0.063	−0.485	0.319	0.209	0.528
DMU_{64}	−0.107	0.061	−0.392	−0.392	−0.094	−0.486	0.499	0.022	0.521
AVERAGE	−0.082	0.050	−0.220	−0.220	−0.048	−0.268	0.356	−0.002	0.354

Appendix B. The results of DEA model treating DMUs as "black box"

Based on Fig. 1 in the paper, we can also create a black box model without loops, which considers the following indicators:

Table B1
The indicators in black box model ($\alpha = 50\%$).

Category	Indicators
Inputs	R&D fund
	Government block fund
	Staff of application of R&D outputs and technology services
Outputs	Number of Students
	Number of SCI/SSCI papers
	$\alpha \times$TI

We define the black-box directional distance (BDD) using the following model (b.1):.

$$BDD^t\left(\mathbf{x}_o^t, \mathbf{y}_o^t; \mathbf{g}_x, \mathbf{g}_y\right) = \max \quad \beta$$
$$\text{subject to}$$
$$\mathbf{x}_o^t - \beta\mathbf{g}_x \geq \sum_{j=1}^{J}\mathbf{x}_j^t\lambda_j^t, \qquad \mathbf{y}_o^t + \beta\mathbf{g}_y \leq \sum_{j=1}^{J}\mathbf{y}_j^t\lambda_j^t, \tag{b.1}$$
$$\boldsymbol{\lambda}^t \geq \mathbf{0}$$

The results are as follows (Table B2):

Table B2
BDD in different years and corresponding rankings.

DMUs	2010		2011		2012		2013	
	Value	Ranking	Value	Ranking	Value	Ranking	Value	Ranking
DMU_1	0.296	35	0.777	2	0.501	43	0.696	1
DMU_2	0.000	57	0.000	58	0.000	58	0.000	61
DMU_3	0.067	52	0.000	58	0.025	56	0.388	27
DMU_4	0.683	5	0.707	9	0.869	2	0.523	13
DMU_5	0.715	1	0.658	15	0.823	5	0.527	12
DMU_6	0.358	32	0.057	56	0.263	53	0.389	26
DMU_7	0.000	57	0.606	18	0.640	30	0.431	23
DMU_8	0.653	8	0.723	7	0.814	7	0.547	11
DMU_9	0.707	2	0.746	6	0.706	19	0.305	39
DMU_{10}	0.019	56	0.439	30	0.619	33	0.213	50
DMU_{11}	0.185	48	0.356	42	0.000	58	0.106	57
DMU_{12}	0.082	51	0.241	48	0.353	52	0.344	31
DMU_{13}	0.000	57	0.000	58	0.000	58	0.000	61
DMU_{14}	0.220	45	0.359	40	0.695	21	0.324	36
DMU_{15}	0.540	20	0.828	1	0.513	42	0.579	7
DMU_{16}	0.638	11	0.688	10	0.644	28	0.647	3
DMU_{17}	0.669	6	0.759	4	0.693	22	0.471	18
DMU_{18}	0.000	57	0.000	58	0.000	58	0.020	60
DMU_{19}	0.604	15	0.388	36	0.672	24	0.315	37
DMU_{20}	0.243	40	0.279	46	0.602	34	0.315	38
DMU_{21}	0.351	33	0.409	33	0.440	48	0.590	6
DMU_{22}	0.390	30	0.449	28	0.769	13	0.367	29
DMU_{23}	0.030	55	0.000	58	0.433	49	0.076	58
DMU_{24}	0.275	38	0.107	53	0.201	54	0.061	59
DMU_{25}	0.169	49	0.362	39	0.532	39	0.366	30
DMU_{26}	0.609	14	0.593	19	0.825	4	0.576	8
DMU_{27}	0.484	23	0.412	32	0.494	45	0.372	28
DMU_{28}	0.234	41	0.065	55	0.000	58	0.248	45
DMU_{29}	0.000	57	0.100	54	0.518	41	0.209	52
DMU_{30}	0.407	29	0.282	45	0.750	16	0.267	41
DMU_{31}	0.223	44	0.379	37	0.643	29	0.266	43
DMU_{32}	0.269	39	0.150	50	0.188	55	0.210	51
DMU_{33}	0.341	34	0.441	29	0.592	35	0.227	48
DMU_{34}	0.652	9	0.687	12	0.847	3	0.475	17

Table B2 (*Continued*)

DMUs	2010		2011		2012		2013	
	Value	Ranking	Value	Ranking	Value	Ranking	Value	Ranking
DMU_{35}	0.226	43	0.137	51	0.424	50	0.331	33
DMU_{36}	0.702	3	0.672	14	0.680	23	0.434	22
DMU_{37}	0.000	57	0.673	13	0.442	47	0.255	44
DMU_{38}	0.473	24	0.493	25	0.671	25	0.441	21
DMU_{39}	0.218	46	0.000	58	0.000	58	0.000	61
DMU_{40}	0.295	36	0.357	41	0.705	20	0.328	34
DMU_{41}	0.000	57	0.235	49	0.631	32	0.225	49
DMU_{42}	0.484	22	0.579	20	0.746	17	0.552	10
DMU_{43}	0.669	7	0.760	3	0.756	14	0.606	4
DMU_{44}	0.486	21	0.562	21	0.669	26	0.332	32
DMU_{45}	0.561	16	0.551	22	0.798	9	0.455	19
DMU_{46}	0.611	13	0.687	11	0.879	1	0.554	9
DMU_{47}	0.229	42	0.278	47	0.553	37	0.496	15
DMU_{48}	0.693	4	0.747	5	0.775	12	0.603	5
DMU_{49}	0.049	53	0.365	38	0.632	31	0.139	56
DMU_{50}	0.560	17	0.467	27	0.663	27	0.407	25
DMU_{51}	0.548	18	0.393	35	0.751	15	0.240	46
DMU_{52}	0.380	31	0.512	24	0.717	18	0.171	54
DMU_{53}	0.432	27	0.477	26	0.796	10	0.517	14
DMU_{54}	0.410	28	0.399	34	0.454	46	0.166	55
DMU_{55}	0.101	50	0.000	58	0.000	58	0.273	40
DMU_{56}	0.205	47	0.302	44	0.412	51	0.204	53
DMU_{57}	0.447	26	0.612	17	0.788	11	0.425	24
DMU_{58}	0.450	25	0.546	23	0.013	57	0.326	35
DMU_{59}	0.295	37	0.315	43	0.555	36	0.266	42
DMU_{60}	0.625	12	0.636	16	0.817	6	0.477	16
DMU_{61}	0.544	19	0.414	31	0.525	40	0.653	2
DMU_{62}	0.639	10	0.710	8	0.803	8	0.443	20
DMU_{63}	0.044	54	0.002	57	0.534	38	0.228	47
DMU_{64}	0.000	57	0.112	52	0.499	44	0.000	61
AVERAGE	0.351		0.407		0.537		0.344	

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