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Evaluation of multi-period regional R&D efficiency: An application of dynamic DEA to China's regional R&D systems

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Highlights

- We model for the multi-period R&D efficiency of regional innovation systems associated with DEA.
- Our model accounts for the productive interdependence between regional R&D activities over periods.
- The linking function of R&D capital stocks within multi-period R&D systems is considered.
- We have evaluated China's regional R&D efficiency over the first five-year period (2006-2010) after the NPMLSTD.

Evaluation of multi-period regional R&D efficiency: An application of dynamic DEA to China's regional R&D systems

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Abstract: The existing studies about regional R&D efficiency measurement in a specific period have not considered the dynamic interdependence between regional R&D activities over different periods. This paper offers a solution to this problem in multi-period regional R&D efficiency measurement with a novel application to China's regional R&D systems. This solution can present a systemic measurement for the overall efficiency score of multi-period regional R&D investment activities, and deduce a weighted decomposition of the overall efficiency score into period efficiency scores. This paper develops a dynamic analytical framework with a new estimation technique from a long-term and systemic perspective associated with data envelopment analysis technique. Our efficiency model with endogenous weights on period efficiencies effectively accounts for the linking function and double role of R&D capital stock in the operation of connected regional R&D systems and the intertemporal dependence of R&D investment on R&D outputs. The R&D capital stock as the carry-over estimated using the perpetual inventory method helps this efficiency model to account for the time lag and multi-period influence of R&D inputs on R&D outputs. This approach is applied to a new database of R&D input-output systems in China's provinces during the first five-year period (2006-2010) after China's National Plan for Medium- and Long-term Scientific and Technological Development (NPMLSTD).

Keywords: Multi-period regional R&D systems; R&D capital stock; Efficiency measurement and decomposition; Data envelopment analysis; perpetual inventory method; China's provincial regions

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1. Introduction

The accurate measurement of regional research and development (R&D) efficiency is an important issue for the improvement of scientific and technological (S&T) investment and management in a multi-region economy. This topic has received increasing academic interest in recent years (see Zabala-Iturriagagoitia et al., 2007; Fu, 2008; Guan and Chen, 2010a; Fritsch and Slavtchev, 2011; Chen and Guan, 2012; Chen and Kou, 2014; Broekel, 2015; Han et al., 2016). However, the published literature on regional R&D efficiency measurement is mainly focused on the cross-section static R&D efficiency in a specific period (e.g., one year). In policy practice, the multi-period efficiency of regional R&D activities over time is usually needed to assess the effectiveness of regional S&T plan implementation over a certain period. This is important for the long-term development of an economy. This is true, especially in regions that adopt a plan-driven development model and continue to invest in R&D activities for several consecutive years (e.g., a five-year period or a ten-year period). Therefore, an evaluation of the overall efficiency of multi-period regional R&D investment is needed for the assessment of a government's performance in the allocation of resources and the management of R&D activities within the whole economy in the time- and space- dimension. However, there is still a gap in this research topic.

In the existing literature, the operations of regional R&D activities are supposed to be independent between different periods, whose efficiency scores are measured separately in each period. One can use the arithmetic (or geometric) average of multi-period efficiency scores to assess the overall performance of R&D processes over multiple periods. However, the operation of one regional R&D process in one period is not independent on that in the next one in practice. There is an interdependence between consecutive periods in regional R&D activities which is created by the linkage of time-intermediate products (also called carry-overs). In a regional R&D process, the regional R&D capital stock functions as a time-intermediate product, which left after researching and developing in previous periods becomes the source for incremental knowledge in subsequent ones. Such time-intermediate products serve as carry-overs from one period to the next, and link the operation of one region across time. In the relational context, the traditional single-period optimization model is not suitable for the performance evaluation from the long-term point of view. Instead, a multi-period optimization model is appropriate.

In terms of the interdependence between regional R&D processes in the productive relationship over multiple periods, this paper proposes a new formulating approach of dynamic data envelopment analysis (DEA) models. The proposed model can be seen as an extension of traditional DEA models over time. The formulation of our model is flexible, which is consistent with the objective assessment principle of DEA modeling without requiring a prior specification of weights on inputs and outputs and/or explicit delineation of assumed functional forms of relations between inputs and outputs (see Banker et al., 1984). The combination weights of component efficiency scores in this approach are not exogenously pre-specified like Tone and Tsutsui (2010), but endogenously derived from the statistical data and self-generated in the calculation process like Kao (2013). In contrast to Kao (2013), this paper's modeling approach not only produces a differential weight set on period efficiencies across regions, but also provides a systems thinking estimation of efficiency scores and makes the comparison between the overall efficiency score and period efficiency scores logical. This study's approach combing with the perpetual inventory method (PIM) can deal with several important questions to be solved in the multi-period regional R&D efficiency measures. The empirical exploration for policy-making is another important purpose in this paper. This approach is applied to a novel database of R&D input-output systems in China's province-level regions during the first five-year period (2006-2010) after China's National Plan for Medium- and Long-term Scientific and Technological Development (NPMLSTD). The empirical exercise carried out in this research will provide useful evidences for the evaluation of the implementation effectiveness of the NPMLSTD.

The rest of this paper is as follows. A literature review of regional R&D efficiency measures with important issues to be solved is implemented in section 2, and a conceptual framework for the dynamic multi-period R&D process is constructed in section 3. A dynamic DEA model for the multi-period regional R&D efficiency is formulated in section 4. An empirical study based on a dataset of R&D activities across China's provincial regions over the five-year (2006-2010) period is presented in section 5. Section 6 concludes the paper.

2. Literature review and important issues to be solved

2.1 Literature review

Most of extant literature is focused on the single-period regional R&D efficiency measurement from a static perspective, which has been implemented in different countries' contexts. Fritsch and Slavtchev (2010, 2011) and Broekel (2012, 2015) focused their attention on Germany region-level R&D efficiency scores. Guan and Chen (2010b), Li et al. (2012) and Chen and Kou (2014) made relevant studies under the empirical context of China. Some papers tried novel extensions in the regional R&D efficiency measurement from the innovation process perspective, which discriminated the upstream knowledge creation subprocess and the downstream knowledge application subprocess (see Guan and Chen, 2010b; Chen and Guan, 2012; Li et al., 2012; Chen and Kou, 2014). In contrast, there is little literature of exploring regional R&D efficiency scores from the dynamic time-dimension perspective. Even Guan and Chen (2010a) and Han et al. (2016) have further modeled the change of regional R&D efficiency, however they did not consider the interrelationship between R&D processes in two consecutive periods. The relevant literature measuring the single-period regional R&D efficiency cannot provide an effective measurement of the multi-period regional R&D efficiency since the interactions between R&D processes over multiple periods were not considered in the single-period static models. So, a new efficiency modeling approach adapted to the specific multi-period regional R&D efficiency measurement is needed.

When modeling for the regional R&D efficiency scores, the program-based deterministic traditional DEA models are usually chosen due to their flexibility (Guan and Chen, 2010a). Examples of these traditional DEA models are CCR (Charnes et al., 1978), BCC (Banker et al., 1984) and SBM (Tone, 2001). The regression-based parametric method is another tool to model the regional R&D efficiency scores (see Fritsch and Slavtchev, 2010, 2011; Bai, 2013), which is not popular due to the requirement of some necessary conditions such as only one output and the specific function relationship between the inputs and the outputs. These conditions usually cannot be satisfied in describing regional R&D activities. There are some special studies in the given contexts, and two regression-based methods have been used. One is the maximum output elasticity approach based on the C-D production function (see Fritsch and Slavtchev, 2010), which, however, ignores the possibility that the values of variables could be affected by measurement errors or by random disturbances (Fritsch and Slavtchev, 2011). So, the maximum output elasticity approach is truly deterministic like traditional DEA models. In order to deal with those unexpected factors, the stochastic frontier analysis (SFA) still is an appropriate model (see Fritsch and Slavtchev, 2011; Bai, 2013), which however, as the maximum output elasticity approach, cannot deal with the interdependence between R&D processes over multiple periods. Until now, it is rare to find that the relevant literature has modeled for the multi-period regional R&D efficiency with the consideration of the interactions between R&D processes over multiple periods.

2.2. Important issues to be solved

In terms of the operating characteristics of R&D processes, there are three interdependence questions which influence the accuracy of measuring multi-period regional R&D efficiency scores. They include “inter-temporal dependence”, “time lag between inputs and outputs” and “multi-period influence”, which create the interdependence between R&D processes/activities in the production relationship over time. If the interdependence is not considered in modeling, some production information influencing the R&D performance may be neglected, which influences the accuracy of multi-period R&D efficiency measurement.

Lagged effects occur when inputs contribute to both current and future output production (Chen and van Dalen, 2010). The time lag structure has always been an important question in analyzing the R&D-patents relationships from earlier studies like Pakes and Griliches (1984) to more recent Wang and Hagedoorn (2014). Because R&D processes need a productive transformation procedure, there is a time lag from R&D inputs to R&D outputs (Guan and Chen, 2010a). One common simple approach to deal with it in modeling the regional R&D efficiency is that one fixed time lag is assumed (see Guan and Chen, 2010b; Chen and Kou, 2014). However, there is still no generally accepted length of the time lag on R&D outputs (Bonaccorsi and Daraio, 2003; Guan and Chen, 2010a).

The multi-period influence is another key question in relating R&D inputs to R&D outputs in addition to the time lag. The time lag is caused by the required time in R&D activities, while the multi-period influence is caused by the capital feature of R&D investment. The multi-period influence may be caused by different time lags for different R&D activities at the regional level. In contrast to other investment, the R&D investment at one period not only influences the R&D outputs in some period by a time lag, but also contributes to these in subsequent periods. This means that the R&D output in one period is the result of the accumulated effect of R&D investment in history. So, only considering the time lag is not enough to track the contributors to R&D outputs.

In contrast to the multi-period influence, the inter-temporal dependence refers to the specific situation where some outputs produced in one period are utilized as inputs in the next period. These outputs are named as “intermediate products” over time, such as R&D capital stocks in the case of this study which make R&D activities in two consecutive periods dependent in the production relationship. The inter-temporal dependence should be considered in the evaluation of the long-term regional R&D efficiency. Since the R&D capital stock has linked together R&D processes over multiple periods into an integrated production system, the modeling approach for it should account for the “linkage” role of it.

Besides, the provision of “systemic measure” is expected since the multi-period regional R&D process is seen as an integrated production system. The overall efficiency of the multi-period regional R&D process is determined together by the period-component efficiency scores of all subprocesses within it, so there is a logical relationship between the overall efficiency score and period-component ones. According to common sense, some of the period-component regional efficiency scores should be above or equal to the overall regional efficiency, and the other should be below or equal to it. It is illogical that the overall regional efficiency score is above or below all period-component regional efficiency scores.

3. Conceptual framework

The R&D process is a knowledge-creation process. This section constructs a conceptual framework for the dynamic R&D process based on a knowledge production thinking of R&D processes over multiple periods. A number of studies exist which focus on particular aspects of the knowledge-creation process within regional innovation systems (Runiewicz-Wardyn, 2013). Most of them are based on the concept of the “knowledge production function” (KPF), a concept Griliches (1979) originally introduced as a tool to measure an input-output relationship of R&D or innovation activities from the production perspective. During the production process of knowledge, the R&D capital stock both embodying knowledge stock and influencing knowledge output plays an interesting double role. According to the definition of the knowledge production function, the R&D capital stock embodying knowledge stock is an accumulated input in the R&D process. Because the current researchers stand “on the shoulders” of previous researchers, we would expect to see that the more knowledge stock is in position, the higher probability of creating new knowledge would be. As argued by Scotchmer (1991), the innovation process is of a cumulative nature such that early innovations (i.e., knowledge stock) provide a boost or a technological foundation for later innovations (i.e., new knowledge) (Wang and Hagedoorn, 2014). The knowledge stock mainly embodies R&D experiences and available R&D facilities accumulated in history.

At the same time, the knowledge capital is the output of knowledge production or R&D investment. As defined by the Frascati Manual (OECD, 1994), the R&D activities comprise creative work undertaken on a systematic basis in order to increase the stock of knowledge. In this document, R&D is defined as “creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications”. Unlike the ordinary physical capital which is formulated just by purchasing and can be employed without further productive activity, the knowledge capital stock is created by R&D investment through a “production procedure” (Huang, 2007). Clearly, the R&D capital stock serves as the input and the output in the knowledge creation process. This means that a complete knowledge production process not only includes the immediate R&D inputs and the incremental outputs in knowledge, but also involves the participation of R&D capital stock in both the input and output sides. See the conceptual process as described in Figure 1.

As demonstrated in Figure 1, the operation of a knowledge creation process is accompanied by the formation of the R&D capital stock (knowledge stock) produced by the former periods and some new immediate inputs, e.g., R&D expenditure and personnel, during which new knowledge stock forms and some new incremental knowledge outputs are produced.

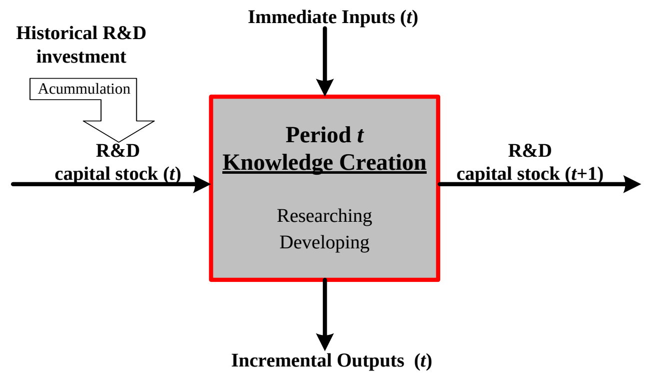


Figure 1. A conceptual process from R&D inputs to outputs in period *t*

Obviously, the R&D capital stock plays a linkage role between two consecutive R&D processes. If considering the R&D processes over T periods, a multi-period regional R&D system forms by the linkage of R&D capital stock. Let $Z_{pj}^{(t)}\ (t=1,2,\cdots,T+1;\ p=1,2,\cdots,q)$ be the R&D capital stock (t) forming in the end of the (t-1)th period over T consecutive periods for the j^{th} region. Without the loss of generality, it is supposed that there are q variables to measure R&D capital stock. There are m independent immediate R&D inputs $X_{ij}^{(t)}\ (t=1,2,\cdots,T;\ i=1,2,\cdots,m)$ and s independent incremental R&D outputs $\sum_{i=1}^{m} v_i X_{ij}^{(t)} + \sum_{p=1}^{q} w_p Z_{pj}^{(t-1)}$ in each period. Thus, we can obtain a multi-period regional R&D input-output production system as shown in Figure 2.

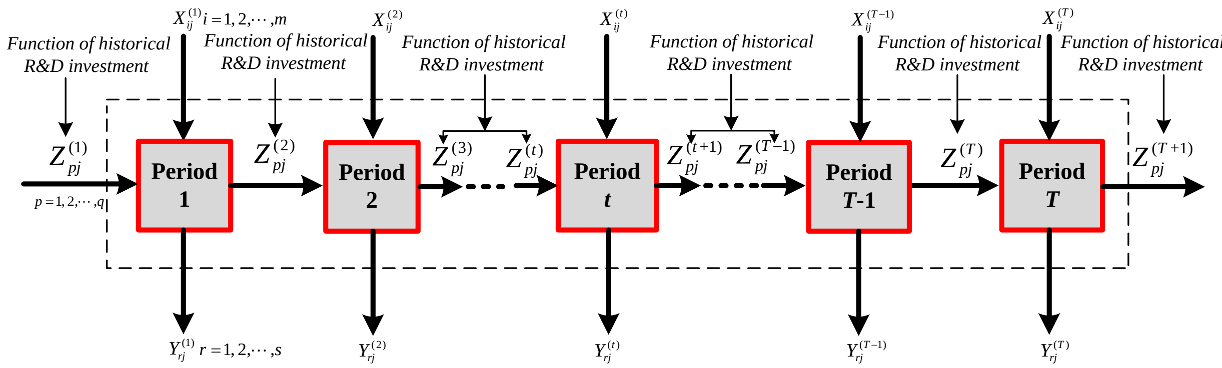


Figure 2. A general framework of the dynamic R&D input-output system over the consecutive *T* periods

As demonstrated in Figure 2, the R&D capital stock $Z_{pj}^{(t)}$ makes the two consecutive R&D processes in periods t-1 and t link in the production relationship. It plays a double identity in the flow of R&D processes, which is the output of the R&D process in period t-1 and the input of the R&D process in period t. The conceptual figure helps in understanding the operational performance of one multi-period regional R&D input-output process from the systemic perspective, which guides us to pay attention to the overall efficiency of R&D input-output processes over multiple periods from the long-term perspective. Obviously, the overall efficiency score is jointly determined by *T* component period efficiency scores over *T* periods. The later discussions in this paper show that there is a convex combination in the mathematic relationship between the overall efficiency score and component ones.

4. Modeling

4.1 Estimation of regional R&D capital stock

Since both time lag and multi-period influence have an effect on the measure of the inputs in one R&D process, the approach of dealing with the two questions should be focused on how to consider all functional components on R&D outputs. The PIM is used to estimate R&D capital stock in this study (see Hall and Mairesse, 1995; Hu and Jefferson, 2004; Guellec and van Pottelsberghe de la Potterie, 2004; Guo, 2008), which can help in retrieving the lost functions of regional R&D investments or accumulated knowledge stock in history.

The basic idea of the PIM is to interpret an economy's capital stock as an inventory. The stock of inventory increases with capital formation (investments). Once an investment has entered an economy's inventory it remains there forever and provides services to the inventory owner. The amount by which the capital stock falls per period is the depreciation rate. However, while the value of the investment decreases in the course of time, it never falls to zero. Thus, an investment principally has a perpetual usefulness (Berlemann and Wesselhöft, 2014). The R&D investment is no exception. Specifically, the basic formula of PIM used to create a stock of R&D capital from a flow of R&D investments is the following equation:

$$K_{(t)} = I_{(t-1)} + (1-\delta) \times K_{(t-1)} \tag{1}$$

where $K_{(t)}$ is the R&D capital stock in the t^{th} year, $I_{(t\text{-}1)}$ is the gross R&D investment in the $(t\text{-}1)^{th}$ year, and δ is the depreciation rate. Repeatedly substituting this equation for the capital stock at the begin of period *t*, $K_{(t\text{-}1)}$, leads to:

$$K_{(t)} = \sum_{i=0}^{\infty} (1-\delta)^i \times I_{(t-(i+1))} \tag{2}$$

Thus, the R&D capital stock in period *t* is a weighted sum of the history of capital stock investments (Berlemann and Wesselhöft, 2014).

The PIM-based measure of R&D capital stocks in the empirical applications is based on some restrictive assumptions, such as a constant productivity of R&D activity, a constant structure of R&D by type of activity and a constant lag structure within types of activity. By formulas (1) and (2), the initial R&D capital stock ($K_{(0)}$) is calculated as:

$$K_{(0)} = \frac{I_{(0)}}{g+\delta} \tag{3}$$

where g is the growth rate for the R&D investment series. The choice of depreciation rate δ for R&D capital makes little difference (Hall and Mairesse, 1995), and an arbitrarily chosen depreciation rate with the usual range from 10% to 15%. Furthermore, just as suggested by Hall and Mairesse (1995) and Hu and Jefferson (2004), the initial R&D capital stock is constructed by assuming a constant growth rate of R&D expenditure.

Since the R&D capital stock can retrieve the lost functions of R&D investments or the accumulated knowledge stock in history, the intertemporal influences from the previous 'old' R&D activities can be considered in our framework. This helps in constructing the linkage between R&D activities over time and leads observers to evaluate and plan R&D activities from the long-term and systemic perspective. Besides, the consideration of R&D capital stock can slow down the impact of sudden huge R&D investments on the efficiency estimation since it plays a more important role in the R&D output (Hall and Mairesse, 1995; Hu and Jefferson, 2004; Chen and Guan, 2011).

4.2 Measurement of the multi-period regional R&D efficiency

As mentioned above, the inter-temporal dependence in fact influences the production relationship of the multi-period R&D system in Figure 2, so we have to choose an appropriate model to cope with it. When multiple periods with inter-relations are involved, the overall efficiency must be measured in a dynamic manner, taking into account the inter-relationship between consecutive periods. Otherwise, the resulting efficiency measures will be misleading. In terms of the multi-input and multi-output characteristics of regional R&D activities as well as the uncertainty of the production relationship between inputs and outputs due to the complexity of regional R&D systems, DEA is preferable to SFA. Here, in terms of the relational multi-stage production process over multiple periods, the dynamic DEA is used to model for the multi-period regional R&D efficiency in this study.

There are two groups of dynamic DEA models in the extant literature, which were developed respectively based on the activity analysis model (Färe and Grosskopf, 1996) and traditional DEA models. The first group has a longer history. In the relevant literature, Färe and Grosskopf's (1996) work became the basis for many later studies on this kind of dynamic DEA. The subsequent literature (e.g., Nemoto and Goto, 2003; Silva and Stefanou, 2007; Chen and van Dalen, 2010; Kapelko et al., 2014; Silva et al., 2015; Yu et al., 2016; Fukuyama et al., 2016) extended Färe and Grosskopf’s (1996) work in many ways. However, most of them can only calculate the overall efficiency, and the period-specific efficiencies must be calculated separately. An attractive property of the second group of studies is that it provides simultaneous measures of the overall efficiency and all period-specific efficiencies. One typical version was proposed by Tone and Tsutsui (2010) based on the traditional SBM model. However, Tone and Tsutsui’s (2010) model needs pre-specified weights on period-efficiency scores. In practice, the relationship between the overall and period efficiencies, which is intuitively expected to exist, is usually not known. In this situation, Kao (2013) novelly proposed a relational dynamic DEA model without pre-specified weights. However, the calculation results of efficiency scores by Kao’s (2013) model cannot meet the property of “systemic measure” (see more discussions and evidences in the following sections). This section proposes a new dynamic DEA model without pre-specified weights to enrich the second group of studies. This new model can satisfy the “systemic measure” and deal with the interdependence between period subprocesses.

DEA is a program-based method. In modeling, the constraint sets in the DEA model determine the production frontier structure of decision-making units (DMUs), and the objective function in it determines the projection way/orientation of the DMU under evaluation on the production frontier. In this study, regions are DMUs. The R&D efficiency score of one DMU is simultaneously determined by both its R&D production frontier structure and projection way in the DEA-based modeling. Since the form of objective function determines the optimal orientation in the R&D efficiency calculation, its formulation needs to fully account for the production information influencing the R&D efficiency performance of the region under evaluation, especially in order to construct an expected combination relationship between the overall R&D efficiency score and period ones. Unlike Kao (2013), this paper fully incorporates the production information embedded on R&D capital stocks as carry-overs into the objective function of the program model for the overall efficiency.

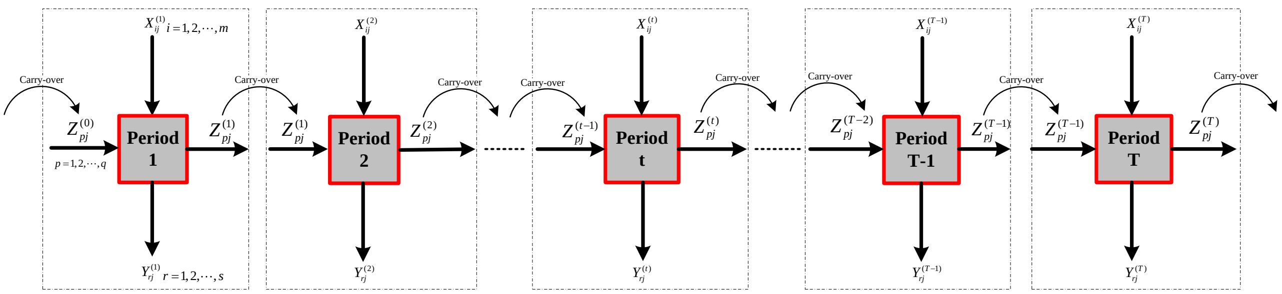


Figure 3. Decomposition of the dynamic multi-period R&D system with carry-overs connecting consecutive periods

To illustrate the modeling approach, Figure 3 is used to display the decomposition of the dynamic regional R&D system with flows connecting two consecutive periods. The decomposed figure can help in more clearly understanding the double-role of R&D capital stocks, $Z_{pj}^{(t)}$ $(t=1,2,\cdots,T+1;\ p=1,2,\cdots,q)$, as carry-overs which are the output of the R&D process in period t-1 and the input of the R&D process in period t. The double identity of R&D capital stocks as carry-overs can transfer previous accumulated knowledge and experience to subsequent periods within the multi-period regional R&D system.

In the t^{th} period, the aggregate R&D inputs and R&D outputs in the j^{th} region respectively are $\sum_{i=1}^{m} v_i X_{ij}^{(t)} + \sum_{p=1}^{q} w_p Z_{pj}^{(t)}$ and $\sum_{r=1}^{s} u_r Y_{rj}^{(t)} + \sum_{p=1}^{q} w_p Z_{pj}^{(t+1)}$ in terms of the double-role of R&D capital stocks in the multi-period regional R&D system. Then, the two additively aggregated terms†, $\sum_{t=1}^{T}\sum_{i=1}^{m} v_i X_{ij}^{(t)} + \sum_{t=1}^{T}\sum_{p=1}^{q} w_p Z_{pj}^{(t)}$ and $\sum_{t=1}^{T}\sum_{r=1}^{s} u_r Y_{rj}^{(t)} + \sum_{t=1}^{T}\sum_{p=1}^{q} w_p Z_{pj}^{(t+1)}$, respectively present the nominal system-wide aggregate R&D inputs and R&D outputs in the whole connected R&D production process over T periods as depicted in Figure 3. Here, the production information embedded on the double-role of R&D capital stocks as the internal carry-over is fully accounted for. As soon as a set of optimal multipliers (u_r^*, v_i^*, w_p^*) is obtained, the overall R&D efficiency E_k of the k^{th} region under evaluation with the production structure as depicted in Figure 2 is represented as

$$E_k = \frac{\sum_{t=1}^{T}\sum_{r=1}^{s} u_r^* Y_{rk}^{(t)} + \sum_{t=1}^{T}\sum_{p=1}^{q} w_p^* Z_{pk}^{(t+1)}}{\sum_{t=1}^{T}\sum_{i=1}^{m} v_i^* X_{ik}^{(t)} + \sum_{t=1}^{T}\sum_{p=1}^{q} w_p^* Z_{pk}^{(t)}} \tag{4}$$

Formula (4) indicates that the overall R&D efficiency E_k is the ratio of the nominal system-wide aggregate R&D inputs to R&D outputs in the time-series R&D production process over T periods as depicted in Figure 3. Following the most favorable perspective of efficiency measurement of the DMU under evaluation in the traditional CCR model (Charnes et al., 1978), the model (5) is formulated to obtain an optimal solution (u_r^*, v_i^*, w_p^*) as multipliers of the k^{th} region under evaluation to aggregate inputs and outputs and calculate the overall R&D efficiency (E_k) under the CRS assumption.

† Inspired by a reviewer's comment, the discounting effect can be considered in aggregating the multiple inputs and outputs of the region under evaluation during multiple periods to account for time preference, which makes our modeling approach applicable in more complex contexts. If a common discount factor (δ^t) for inputs, outputs and carry-overs is available for the DMU under evaluation in the t^{th} period, the discounted nominal system-wide aggregate inputs and outputs in the whole production process over T periods may be respectively $\sum_{t=1}^{T}\delta^t\sum_{i=1}^{m} v_i X_{ij}^{(t)} + \sum_{t=1}^{T}\delta^t\sum_{p=1}^{q} w_p Z_{pj}^{(t)}$ and $\sum_{t=1}^{T}\delta^t\sum_{r=1}^{s} u_r Y_{rj}^{(t)} + \sum_{t=1}^{T}\delta^t\sum_{p=1}^{q} w_p Z_{pj}^{(t+1)}$ (see Nemoto and Goto, 2003; Fukuyama and Weber, 2015; Fukuyama et al., 2016 for more discussions about the discount factor). An existing measure $\delta^t = 1/(1+R)^t$ may be an expected choice, where R is the rate of time preference (see Fukuyama and Weber, 2015; Fukuyama et al., 2016). It is easily proved that the following formulas (4) - (11) still hold with the incorporation of the discounting factor as above.

$$E_k = \max \frac{\sum_{t=1}^{T}\sum_{r=1}^{s} u_r Y_{rk}^{(t)} + \sum_{t=1}^{T}\sum_{p=1}^{q} w_p Z_{pk}^{(t+1)}}{\sum_{t=1}^{T}\sum_{i=1}^{m} v_i X_{ik}^{(t)} + \sum_{t=1}^{T}\sum_{p=1}^{q} w_p Z_{pk}^{(t)}}$$

$$s.t. \quad \frac{\sum_{t=1}^{T}\sum_{r=1}^{s} u_r Y_{rj}^{(t)} + \sum_{t=1}^{T}\sum_{p=1}^{q} w_p Z_{pj}^{(t+1)}}{\sum_{t=1}^{T}\sum_{i=1}^{m} v_i X_{ij}^{(t)} + \sum_{t=1}^{T}\sum_{p=1}^{q} w_p Z_{pj}^{(t)}} \le 1,\ j = 1, 2, \cdots, n \tag{5}$$

$$\frac{\sum_{r=1}^{s} u_r Y_{rj}^{(t)} + \sum_{p=1}^{q} w_p Z_{pj}^{(t+1)}}{\sum_{i=1}^{m} v_i X_{ij}^{(t)} + \sum_{p=1}^{q} w_p Z_{pj}^{(t)}} \le 1,\ t = 1, 2, \cdots, T;\ \ j = 1, 2, \cdots, n$$

$$u_r, v_i, w_p \ge \varepsilon.$$

In the model (5), the first set of n constraints is on the whole R&D production process over T periods of each region, and the second set of nT constraints is on the individual R&D production process of each region in each period. The first set of constraints makes E_k be in (0, 1]. The whole R&D production process of the k^{th} region under evaluation over T periods is efficient when E_k is equal to one.

One attractive advantage of the model (5) is that it can fully incorporate the double-role carry-overs of the variable R&D capital stock during the whole operation of dynamic R&D input-output system with T periods, which can account for more operational information during the dynamic multi-period region-level R&D system. Like the CCR model, the model (5) can be reduced to the equivalent linear form in virtue of the Charnes and Cooper's (1962) transformation for the optimal multipliers (u_r^*, v_i^*, w_p^*). After the optimal multipliers of the k^{th} region under evaluation are obtained, the formula (4) can be used to calculate its overall efficiency score, and further use the formula (6)

$$E_k^{(t)} = \frac{\sum_{r=1}^{s} u_r^* Y_{rk}^{(t)} + \sum_{p=1}^{q} w_p^* Z_{pk}^{(t+1)}}{\sum_{i=1}^{m} v_i^* X_{ik}^{(t)} + \sum_{p=1}^{q} w_p^* Z_{pk}^{(t)}}, \qquad t = 1, 2, \cdots, T \tag{6}$$

to calculate its period (component) efficiencies. The second set of constraints in the model (5) makes $E_k^{(t)} (t = 1, 2, \cdots, T)$ be in (0, 1]. The individual R&D production process of the k^{th} region under evaluation in the t^{th} period is efficient when $E_k^{(t)} (t = 1, 2, \cdots, T)$ is equal to one.

It should be noted that if the proposed model (5) has unique optimal solutions, the overall and period efficiency scores of the k^{th} region under evaluation can be obtained respectively by the formulas (4) and (6). However, in the case of multiple optimal solutions, unique efficiency scores can be obtained according to decision maker's desired preferences or post-program methods such as the one proposed by Tone and Tsutsui (2014).

One of our motivations for this study is to extend and improve Kao's (2013) approach. In order to show the difference in the model formulation, the input-oriented formula of Kao's (2013) model is formulated in this paper and here named as Kao-DDEA model (see Appendix). The difference between this study's new model and the input-oriented version of Kao's (2013) model is discussed in following sections.

4.3 The relationship between the overall R&D efficiency and period R&D efficiencies

Since the sum of the surplus variables associated with T periods is equal to the surplus variables associated with the overall R&D system for the k^{th} region under evaluation, one has:

$$\begin{aligned}&\left(\sum_{t=1}^{T}\sum_{r=1}^{s}u_r^*Y_{rk}^{(t)}+\sum_{t=1}^{T}\sum_{p=1}^{q}w_p^*Z_{pk}^{(t+1)}\right)-\left(\sum_{t=1}^{T}\sum_{i=1}^{m}v_i^*X_{ik}^{(t)}+\sum_{t=1}^{T}\sum_{p=1}^{q}w_p^*Z_{pk}^{(t)}\right)\\&=\sum_{t=1}^{T}\left[\left(\sum_{r=1}^{s}u_r^*Y_{rk}^{(t)}+\sum_{p=1}^{q}w_p^*Z_{pk}^{(t+1)}\right)-\left(\sum_{i=1}^{m}v_i^*X_{ik}^{(t)}+\sum_{p=1}^{q}w_p^*Z_{pk}^{(t)}\right)\right]\end{aligned}\tag{7}$$

Dividing both sides by $\left(\sum_{t=1}^{T}\sum_{i=1}^{m}v_i^*X_{ik}^{(t)}+\sum_{t=1}^{T}\sum_{p=1}^{q}w_p^*Z_{pk}^{(t)}\right)$ results in:

$$\begin{aligned}&1-\frac{\left(\sum_{t=1}^{T}\sum_{r=1}^{s}u_r^*Y_{rk}^{(t)}+\sum_{t=1}^{T}\sum_{p=1}^{q}w_p^*Z_{pk}^{(t+1)}\right)}{\left(\sum_{t=1}^{T}\sum_{i=1}^{m}v_i^*X_{ik}^{(t)}+\sum_{t=1}^{T}\sum_{p=1}^{q}w_p^*Z_{pk}^{(t)}\right)}=\\&\sum_{t=1}^{T}\frac{\left(\sum_{i=1}^{m}v_i^*X_{ik}^{(t)}+\sum_{p=1}^{q}w_p^*Z_{pk}^{(t)}\right)}{\left(\sum_{t=1}^{T}\sum_{i=1}^{m}v_i^*X_{ik}^{(t)}+\sum_{t=1}^{T}\sum_{p=1}^{q}w_p^*Z_{pk}^{(t)}\right)}\cdot\left(1-\frac{\left(\sum_{r=1}^{s}u_r^*Y_{rk}^{(t)}+\sum_{p=1}^{q}w_p^*Z_{pk}^{(t+1)}\right)}{\left(\sum_{i=1}^{m}v_i^*X_{ik}^{(t)}+\sum_{p=1}^{q}w_p^*Z_{pk}^{(t)}\right)}\right)\end{aligned}\tag{8}$$

Associated with the formulas (4), (6) and (8), the following formula can be obtained:

$$1-E_k=\sum_{t=1}^{T}\omega_k^{(t)}(1-E_k^{(t)})\tag{9}$$

The decomposed period weights

$$\omega_k^{(t)}=\frac{\sum_{i=1}^{m}v_i^*X_{ik}^{(t)}+\sum_{p=1}^{q}w_p^*Z_{pk}^{(t)}}{\sum_{t=1}^{T}\sum_{i=1}^{m}v_i^*X_{ik}^{(t)}+\sum_{t=1}^{T}\sum_{p=1}^{q}w_p^*Z_{pk}^{(t)}},\quad t=1,2,\cdots,T\tag{10}$$

represent the importance of the t^{th} period efficiency performance in maximizing the overall R&D efficiency under the CRS assumption. The weight coefficients for combination reflect the "share" of the virtual aggregate input during the corresponding period against the virtual aggregate input during the whole multi-period R&D system. As expected, it is easy to deduce that the sum of weights is one, i.e., $\sum_{t=1}^{T}\omega_k^{(t)}=1$ holds in this study, which is endogenously based on the statistical datasets. Another advantage of the weights produced by the formula (10) is to take into account the cross-region differences and provide a fair comparison platform. In our analytical framework, each region has obtained one different weight set combining period efficiencies. The weight set of each region is produced by differently combining given input and output indicators in it from the relative advantage perspective, which leads to maximizing the overall R&D efficiency of it. In this context, the controversy across regions in the choice of one common weight set can be avoided.

Since $\sum_{t=1}^{T}\omega_k^{(t)}=1$, then $1-E_k=\sum_{t=1}^{T}\omega_k^{(t)}(1-E_k^{(t)})=1-\sum_{t=1}^{T}\omega_k^{(t)}E_k^{(t)}$ exist. We can obtain:

$$E_k=\sum_{t=1}^{T}\omega_k^{(t)}E_k^{(t)} \tag{11}$$

This means the overall regional R&D efficiency is a convex combination of component (period) R&D efficiencies in this study's modeling approach. So, the proposed approach presents a desirable aggregation way of component efficiencies into the overall efficiency of regional R&D processes. If $E_k^{\min}$ and $E_k^{\max}$ is respectively the minimum and maximum of period efficiency scores $E_k^{(t)}$ ($t=1,2,\cdots,T$), then $E_k=\sum_{t=1}^{T}\omega_k^{(t)}E_k^{(t)}\le E_k^{\max}\cdot\sum_{t=1}^{T}\omega_k^{(t)}=E_k^{\max}$ and $E_k=\sum_{t=1}^{T}\omega_k^{(t)}E_k^{\min}\ge E_k^{\min}\cdot\sum_{t=1}^{T}\omega_k^{(t)}=E_k^{\min}$ by $\sum_{t=1}^{h}\omega^{(t)}=1$. This means that this study's efficiency measures satisfy the property of "systemic measure" and are logical in the comparison of the overall efficiency score of one regional R&D system with period efficiency scores within it. This attracting systemic property or rule exists in Tone and Tsutsui's (2010) approach, but does not always exist for Kao's (2013) approach (see the proof in Appendix). The essential reason is that the formulation of objective function in Kao's (2013) model cannot consider the internal production information embedded on R&D capital stocks as carry-overs within the multi-period R&D process. However, this study's modeling approach is similar to Kao's (2013) approach using a set of endogenous weights generated automatically based on statistical data from the most favorable perspective for the region under evaluation. This is also different from Tone and Tsutsui (2010), where a set of pre-specified weights are exogenously supplied. The common pre-specified weight set for any region is usually controversial when implementing a comparison across different regions, and it is difficult and unfair to specify the exogenous weights agreeable to all regions.

Moreover, our modeling approach is applicable under the variable returns to scale (VRS). When the production returns to scale difference across periods is accounted for, the scale inefficiency element contained in the CRS inefficiency should be removed to obtain pure technical efficiency. Inspired by the formulating way of Banker et al.'s (1984) BCC model, the scale inefficiency variable $\mu_k^{(t)}$ ($t=1,2,\cdots,T$) in the t^{th} period should be eliminated from the visual outputs in defining the overall efficiency under VRS assumption. In this situation, the R&D outputs in the t^{th} period are $\sum_{r=1}^{s} u_r Y_{rj}^{(t)} + \sum_{p=1}^{q} w_p Z_{pj}^{(t)} - \mu_k^{(t)}$, $t = 1, 2, \cdots, T$. Then, the additively aggregated term, $\sum_{t=1}^{T} \sum_{r=1}^{s} u_r Y_{rj}^{(t)} + \sum_{t=1}^{T} \sum_{p=1}^{q} w_p Z_{pj}^{(t+1)} - \sum_{t=1}^{T} \mu_k^{(t)}$, present the nominal system-wide aggregate output of the whole regional R&D production process over T periods under VRS assumption, where formulas (4) - (11) hold with the elimination of the scale inefficiency variable $\mu_k^{(t)}$ ($t = 1, 2, \cdots, T$) from the visual outputs.

5. Empirical analysis

China's provinces are chosen as analysis units in this study. The province-level regions in China are administratively and economically independent geographical regions, and both the mobilization of labor forces and the operation of the whole innovation process happen more often from within rather than between province-level regions (Li, 2009; Chen and Guan, 2012). So, it is appropriate and advisable to empirically investigate China's R&D system based on the province-level datasets. Specifically, a novel province-year panel dataset over the first five-year period (2006-2010) after the implementation of China's National Plan for Medium-term and Long-term Scientific and Technological Development (NPMLSTD) is used to support this empirical study and provide an evaluation of the efficiency performance of China's regional R&D systems. In order to promote the strategy of constructing an innovative country in 2020, the Chinese government promulgated the NPMLSTD beginning in 2006. In this context, increasing R&D resources are invested with a bigger growth rate reaching to 706.26 billion RMB in 2010. The full-time equivalent of R&D staff increased to 2.55 million man-years in 2010, which is the highest in the world. The efficiency performance of such large R&D investment in this five-year period obviously attracts the attention of policy-makers and academic researchers, which is needed in guiding the allocation of R&D resources across provinces or periods. We select 29 of China's provinces as our observed sample, but other provinces (Tibet, Hainan, Hong Kong, Macao and Taiwan) are not included due to the lack of data.

5.1 Indicators and measures

A R&D process is the knowledge creation/production process, which mainly includes two kinds of immediate inputs. One is the R&D personnel (RD_P) as the efforts in intellectual activities, and the other is the R&D expenditure (RD_E) as the supporting input including the payment of R&D

employees’ wages and the purchase of R&D equipment and facilities (see Table 1). The RD_P is measured by the full-time equivalent of R&D personnel in the observed region in the tested year, while the RD_E is measured by the expenditure on R&D activities in this region in the same year (see Chen and Guan, 2011). We deflate RD_E to the year 2005 using China’s Consumer Price Index.

In the incremental output of the R&D process, two kinds of outputs are commonly selected. One is the output of scientific knowledge, and the other is the output of technological inventions. The published science citation index (SCI) papers (PAP) and the domestically granted patents (PAT) are used as new incremental outputs during the observed period for each region in this study (see Table 1). In the output of scientific R&D activities, papers should be the most appropriate choice in terms of data availability and measurement accuracy. Compared with patenting activities, paper publication activities are more international in China. In addition of the consideration of innovation quality, we use the number of SCI articles published during the observation year as the proxy of PAP[‡] (see Guan and Chen, 2012). In terms of the output of technological R&D activities, patents have so far been the most appropriate indicator to date (e.g., Fritsch and Slavtchev, 2010; Li 2009). In the consideration of the localization of patenting activities, the PAT is measured by the number of domestic patents granted in the observed region in the tested year which includes invention, utility model and design patents.

Table 1. Measure indicators of the regional R&D process

Indicators	Full indicator name	Role in R&D process	Description and measure	Data Source
RD_E	R&D expenditure	Input	The incremental R&D expenditure during the observation year	CSYST[a]
RD_P	R&D personnel	Input	The full-time equivalent (FTE) measures of the R&D personnel input during the observation year	CSYST
RD_CS	R&D capital stock	Carry-over	The accumulated R&D expenditure before the observation year by the PIM	CSYST
PAP	SCI papers	Output	The number of science citation index (SCI) articles published during the observation year	CSYST
PAT	Domestic granted patents	Output	The number of domestic patents granted in the observed region during the observation year	CSYST

[a.] CSYST: China Statistical Yearbook on Science and Technology

We use the PIM to estimate the RD_CS based on the previous time series of R&D expenditure with the year 2005 as the initial period. To be attractive, the R&D stock capital measured by PIM as one output in our analytical framework, to some degree, can restrict some R&D outputs not resulting in patents and papers since it is directly measured by accumulative R&D investment. A depreciation rate of 15 percent and a presample growth rate of 5 percent in real R&D expenditure are assumed (see Guo, 2008; Chen and Guan, 2011).

All data resources are collected from the China Statistical Yearbook on Science and Technology (CSYST) published by the China Statistics Press. We have carried out a trend analysis of

[‡] The domestically published papers are not considered due to the significant correlation between them and SCI papers.

all data to detect and visually screen whether there are sudden changes in the value of a variable over time. Moreover, the residual analysis is also carried out to further detect outliers outside standard deviation where the expected value of standardized residual is below 3. Luckily, we do not find the presence of outliers in our sample. The descriptive statistics of indicators in this study are reported in Table B1 in the Appendix.

5.2 Efficiency estimations

Table 2 reports the calculated efficiency results by our dynamic DEA model. Following Tone and Tsutsui (2014), we use a post-program method and check the uniqueness of efficiency scores, and found no multiple solutions in our sample. In order to clarify the creditability and rationality of the calculated efficiency results by our dynamic DEA model in evaluating the efficiency performance of R&D activities over periods, the calculated results by the CCR model and the Kao-DDEA model are compared with those by our model under the CRS assumption (See Table B2 in the Appendix for the detailed efficiency scores estimated by the CCR model and the Kao-DDEA model in each year). The CCR model can present separate measures of technical efficiency scores for each period. The overall efficiency score by the CCR model is the arithmetic average of period efficiency scores during the five years (see the second column in Table 2). While the overall efficiency score by Kao-DDEA for each region (see the fourth column in Table 2) can be directly obtained by an aggregated model (see A.1 in the Appendix) like this study's model. Since the efficiency calculation in this study is implemented from the optimal perspective of the whole regional R&D processes over the five-year period, it is possible that no province is efficient in the period efficiency scores for some years. This is true in 2006 and 2008. Since some period efficiency scores in some years are not efficient, there are no efficient regions over the whole five-year period in this study's modeling from the systemic perspective. In contrast to Tone and Tsutsui (2010) where the weights are common cross regions, the weights in this study's model are not common across both regions and years (see Table 2). Since different regions may differ in the management model and development strategy of R&D processes over the five-year period, the differential weights are appropriate and fair. In practice, it is usually difficult to pre-specify weights since the importance of each period is not easily understood and measured.

As displayed in Table 2, all provinces are comparable in the overall efficiency score in this model, while seven of twenty-nine provinces are efficient in the CCR model and are not discriminative. Moreover, an obvious differential ranking result of efficiency scores across provinces is produced in this study's model. This means that, in contrast to the CCR model, this study's model can fully account for the inefficiency within the multi-period regional R&D process. For example, three efficient provinces, Beijing, I.Mongolia and Jilin, in the CCR model ranked as the later ones in the ranking, whose rank number is 29, 25 and 26 in this study's model. The nonparametric tests by the Mann-Whitney U and Kolmogorov-Smirnov test in Table 3 show that there is a significant difference in ranking at the average between the two different models. To further investigate the difference, the equality of two distributions of efficiency scores is analyzed by means of non-parametric Kernel density estimation techniques, following Li (1996) and Simar and Zelenyuk (2006). The statistical significance of the difference is further confirmed by a significant Simar-Zelenyuk-adapted Li test value 13.217 ($p < 0.0001$) (see Table 3).

Table 2. Calculated results assuming constant returns to scale

Provinces	Efficiency scores and ranks											Weights						
	CCR		Kao-DDEA		Our model							Our model						Kao-DDEA
	Overall	Rank	Overall	Rank	Overall	Rank	2006	2007	2008	2009	2010	2006	2007	2008	2009	2010	Sum	Sum
Beijing	1.0000	1-7	0.9030	12	0.9182	29	0.9299	0.9255	0.9401	0.8987	0.9079	0.1420	0.1696	0.1945	0.2301	0.2637	1.0000	3.3991
Tianjin	1.0000	1-7	0.9229	5	0.9753	4	0.9677	0.9933	0.9623	0.9883	0.9671	0.1226	0.1526	0.1944	0.2361	0.2943	1.0000	3.1163
Hebei	0.9902	11	0.8944	20	0.9666	11	0.9548	0.9878	0.9696	0.9473	0.9744	0.1269	0.1565	0.1948	0.2392	0.2826	1.0000	3.1655
Shanxi	0.9743	27	0.8823	23	0.9603	21	0.9258	0.9461	0.9658	0.9441	0.9926	0.1253	0.1534	0.1898	0.2415	0.2901	1.0000	3.0014
I.Mongolia	1.0000	1-7	0.8869	22	0.9568	25	0.9434	0.9440	0.9605	0.9103	1.0000	0.0999	0.1343	0.1798	0.2554	0.3307	1.0000	2.6260
Liaoning	0.9931	9	0.8752	25	0.9622	18	0.9822	0.9596	0.9712	0.9464	0.9605	0.1408	0.1691	0.1954	0.2298	0.2649	1.0000	3.3047
Jilin	1.0000	1-7	0.9107	8	0.9565	26	0.9863	0.9485	0.9781	0.9322	0.9498	0.1465	0.1749	0.1959	0.2280	0.2547	1.0000	1.0600
Heilongjiang	0.9872	19	0.8966	17	0.9671	10	0.9848	0.9827	0.9484	0.9455	0.9816	0.1275	0.1582	0.1960	0.2375	0.2808	1.0000	3.1608
Shanghai	1.0000	1-7	0.9588	3	0.9868	2	0.9806	0.9984	0.9990	0.9667	0.9917	0.1351	0.1632	0.1953	0.2354	0.2710	1.0000	3.1299
Jiangsu	0.9921	10	0.9367	4	0.9589	23	0.9313	0.9538	0.9361	0.9642	0.9841	0.1249	0.1535	0.1931	0.2373	0.2912	1.0000	3.0628
Zhejiang	1.0000	1-7	0.9874	1	0.9956	1	0.9678	1.0000	0.9980	1.0000	0.9993	0.1198	0.1520	0.1932	0.2403	0.2946	1.0000	2.8402
Anhui	0.9866	20	0.8993	13	0.9653	14	0.9604	0.9809	0.9452	0.9380	0.9949	0.1254	0.1523	0.1916	0.2395	0.2912	1.0000	2.8943
Fujian	0.9745	26	0.8797	24	0.9607	20	0.9587	0.9734	0.9650	0.9383	0.9702	0.1311	0.1579	0.1915	0.2360	0.2835	1.0000	3.0702
Jiangxi	0.9889	16	0.8946	19	0.9654	13	0.9471	0.9637	0.9620	0.9617	0.9792	0.1212	0.1523	0.1926	0.2408	0.2931	1.0000	3.0554
Shandong	0.9958	8	0.9220	6	0.9741	5	0.9834	0.9640	0.9548	0.9857	0.9787	0.1189	0.1517	0.1922	0.2372	0.2999	1.0000	3.0198
Henan	0.9828	22	0.8960	18	0.9639	16	0.9308	0.9796	0.9867	0.9244	0.9875	0.1187	0.1480	0.1875	0.2464	0.2994	1.0000	2.9280
Hubei	0.9899	13	0.8973	16	0.9647	15	0.9616	0.9847	0.9550	0.9305	0.9900	0.1243	0.1525	0.1907	0.2403	0.2922	1.0000	2.8789
Hunan	0.9898	14	0.8976	15	0.9633	17	0.9674	0.9446	0.9299	0.9525	1.0000	0.1204	0.1492	0.1877	0.2393	0.3035	1.0000	2.7538
Guangdong	0.9901	12	0.9124	7	0.9655	12	0.9555	0.9650	0.9718	0.9486	0.9799	0.1285	0.1567	0.1903	0.2374	0.2871	1.0000	2.9656
Guangxi	0.9726	28	0.8600	28	0.9503	27	0.9611	0.9768	0.9269	0.9269	0.9660	0.1215	0.1478	0.1882	0.2385	0.3039	1.0000	2.8321
Chongqing	0.9852	21	0.9069	11	0.9693	8	0.9953	0.9680	0.9687	0.9466	0.9779	0.1238	0.1560	0.1910	0.2384	0.2908	1.0000	3.0364
Sichuan	0.9797	24	0.8710	26	0.9590	22	0.9661	0.9423	0.9723	0.9348	0.9772	0.1393	0.1671	0.1921	0.2320	0.2694	1.0000	3.1493
Guizhou	0.9826	23	0.8993	14	0.9675	9	0.9913	0.9897	0.9392	0.9279	0.9971	0.1321	0.1595	0.1950	0.2361	0.2774	1.0000	3.1101
Yunan	0.9888	17	0.9074	10	0.9707	6	0.9690	0.9773	0.9805	0.9587	0.9711	0.1266	0.1580	0.1940	0.2381	0.2833	1.0000	3.1689
Shaanxi	0.9892	15	0.8653	27	0.9585	24	0.9700	0.9522	0.9593	0.9317	0.9792	0.1430	0.1695	0.1950	0.2303	0.2622	1.0000	3.2449
Gansu	1.0000	1-7	0.9763	2	0.9770	3	0.9178	1.0000	0.9842	0.9712	1.0000	0.1639	0.1762	0.1986	0.2232	0.2380	1.0000	1.0307
Qinghai	0.9640	29	0.8106	29	0.9377	28	0.9640	0.9660	0.9792	0.8472	0.9578	0.1398	0.1642	0.1865	0.2379	0.2717	1.0000	3.0408
Ningxia	0.9789	25	0.9092	9	0.9698	7	0.8843	0.9474	0.9985	0.9781	0.9920	0.1234	0.1504	0.1894	0.2429	0.2939	1.0000	3.0208
Xinjiang	0.9883	18	0.8887	21	0.9612	19	0.9488	0.9875	0.9149	0.9487	0.9929	0.1273	0.1493	0.1910	0.2361	0.2962	1.0000	2.8728

Table 3. Comparative analyses between our model and CCR model/Kao-DDEA model in the average efficiency over the 2006-2010 year period

Method		Our model vs CCR model	Our model vs Kao-DDEA model
Mann-Whitney U test	Z Value	-5.751	-5.560
	Probability	(0.000)	(0.000)
Kolmogorov-Smirnov test	Z Value	3.020	3.283
	Probability	(0.000)	(0.000)
Simar-Zelenyuk-adapted Li test	Z Value	13.217	15.469
	Probability	(0.000)	(0.000)

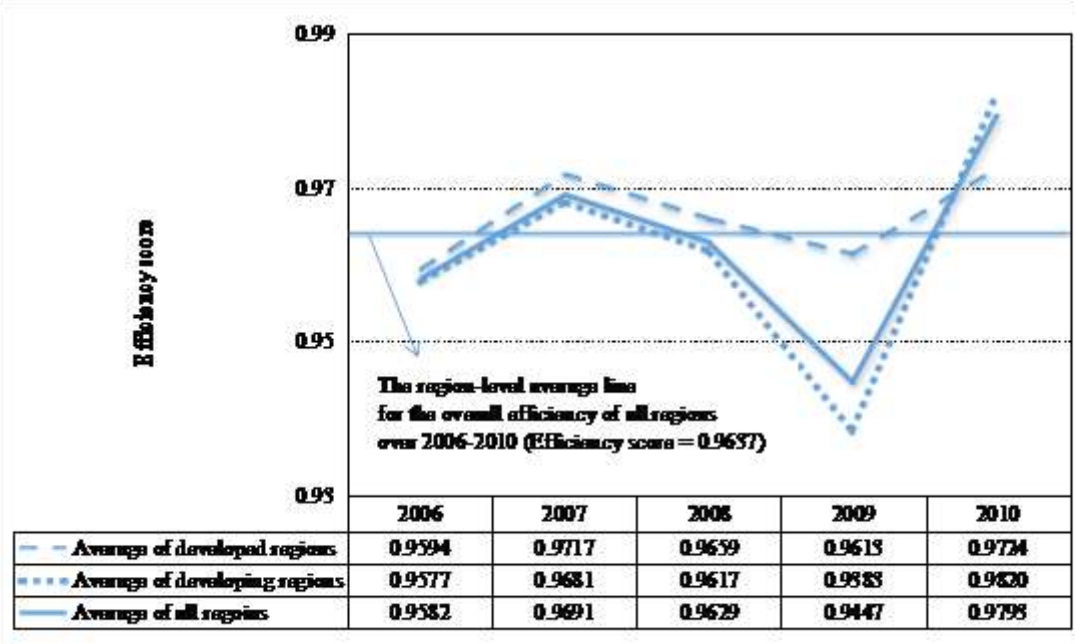
More attractive, compared with the Kao-DDEA model, the ranking difference in our model is significant at the average level, which can be proved by the significant nonparametric test results by the Mann-Whitney U and Kolmogorov-Smirnov test in Table 3. A significant Simar-Zelenyuk-adapted Li test value 15.469 ($p<0.0001$) (see Table 3) further confirms the statistical significance of the difference. There is a difference of above 15 in the rank number between the two approaches for several provinces, such as Beijing, Jilin and Jiangsu. Only the ranking of Zhejiang province in our model is identical to that in the Kao-DDEA model. This means that the consideration of R&D capital stock is needed in measuring the multi-period regional R&D efficiency.

In contrast to the Kao-DDEA model, the results in this study confirm that our model makes sense of the numerical size comparison between the overall efficiency and period-specific ones. Only four provinces, Jilin, Zhejiang, Ningxia and Gansu (see the detailed efficiency scores reported in Table B2 in the Appendix) in the context of the Kao-DDEA model have such efficiency results satisfying the attractive relationship. Comparing the reported results in the last two columns in Table 2, it is clear that the sum of weights generated from our model is one, which makes the combination of period efficiency scores to the overall efficiency score be convex. The convex combination makes the comparison between overall and period regional R&D efficiency scores understandable. However, in the Kao-DDEA model, the sum of weights for most provinces is above three, and that for only two of twenty-nine provinces (Jilin and Gansu) is nearly one. An interesting point in common is that the endogenous period weights from our model (see Table 2) and the Kao-DDEA model (see Table B2 in the Appendix) show an increasing trend. This is reasonable since the present is more important than the past (see Briec and Kerstens, 2009; Tone and Tsutsui, 2014).

The regional efficiency results by our model present some novel findings. Firstly, we find that no regions are efficient in the general operation of R&D production systems over the first five-year period of China's NPMLSTD. Besides, we find that the average of the overall efficiency (value=0.9669) for Chinese developed regions (including Zhejiang, Shanghai, Tianjin, Shandong, Guangdong, Fujian, Jiangsu and Beijing) mainly located in the Eastern coast of China is bigger than that (value=0.9625) for the other 21 developing provinces in the Midwest inland of China. Figure 4 shows that the advantage of developed regions in the average efficiency score still exists for component (period) efficiency scores except for 2010. As proved in some literature such as Fritsch and Slavtchev (2011), Broekel (2012, 2015) and Chen and Kou (2014), the favorable innovation environmental factors can improve the regional R&D efficiency. In China, developed regions usually tend to have a more favorable “hard” innovation environment (e.g., information technology, education and training, and industry cluster) than developing ones. However, it has to be recognized that some exceptional provinces in the Eastern coast (e.g., Beijing, Jiangsu and Fujian) got only an inferior efficiency ranking although they have the superior “hard” innovation environment, while other province (e.g., Gansu, Ningxia and Guizhou) got a superior efficiency ranking although they have an inferior “hard” innovation environment. This result shows that the “hard” innovation environment is not the determinant factor. The “soft” innovation environment related to institutions is usually considered to be a more important factor, which directly influences the process management of R&D activities. In China, the institution of science and technology is always seen as a critical factor in China’s science and technology system (Cao et al., 2013; Fu, 2015). Based on OECD’s investigations (OECD, 2008), the inefficiency in the R&D production frontier performance in China’s national innovation system is never taken away from the inefficiency or deficiency of the “soft factors” for innovation, such as innovation policy instruments (especially about intellectual property rights), public innovation awareness and managerial skills. This finding should be given more attention when making regional policies. It reminds policy-makers that a region-specific policy system is needed in China according to the different innovation contexts and performance levels of regions’ R&D activities.

Figure 4 shows that the region-level average of efficiency scores during the first five-year period (2006-2010) after the implementation of the NPMLSTD displays a fluctuating “N” shape, which is true for the average of developed regions, developing regions or all regions. The first rising, then falling and rising again trend may have a complex underlying reason, which is out of the remit of discussion in this paper. One possible explanation is that this trend may embody the endogenous property of the efficiency change from 2006 to 2010. The growth trend from 2006 to 2007 should be a lock-in continuous movement of R&D efficiency improvement, while the declining trend from 2007 to 2009 possibly contributed to the ineffective application or allocations of the sudden input of R&D expenditure as well as the lagging nature of R&D outputs at the region-average level. Subsequently, the declining trend changes to growth due to the adaptation to the sudden input of

R&D expenditure as well as the coming into effect of the sudden input of R&D expenditures at the region-average level.



	2006	2007	2008	2009	2010
Average of developed regions	0.9594	0.9717	0.9659	0.9615	0.9734
Average of developing regions	0.9577	0.9681	0.9617	0.9383	0.9820
Average of all regions	0.9582	0.9691	0.9629	0.9447	0.9798

Figure 4. Trend of the region-level average of period R&D efficiency scores over the 2006-2010 year period

6. Conclusions and discussions

This study attempts to solve the modeling problem in the overall efficiency measurement of regional R&D activities over multiple periods from the dynamic and systemic perspective. This paper formulates a new dynamic DEA model to estimate the overall efficiency of multi-period regional R&D activities by fully incorporating the production information embedded on R&D capital stocks as carry-overs into the objective function. The proposed efficiency model can deal with the inter-temporal dependence cross periods, time lag between inputs and outputs as well as multi-period influence in R&D processes over time associated with the PIM.

This paper has also constructed a five-year dynamic R&D system from R&D inputs to R&D outputs over 2006-2010 years and empirically evaluated the R&D efficiency in China's province-level regions during the first five-year period after China's National Plan for Medium-term and Long-term Scientific and Technological Development (NPMLSTD). Empirical evidence of the implementation effectiveness of China's NPMLSTD which has useful policy implications is presented.

The DEA model is seen as an objective and fair assessment technique. Our formulating approach of dynamic DEA reserves this advantage in obtaining weights to combine component efficiency scores into the overall one. A set of post-decomposed weights on period efficiencies are obtained in our modeling, which are specific to the DMU under evaluation. This is different to Tone and Tsutsui (2010) where a set of pre-specified weights is exogenously supplied and are common for all DMUs. In practice, it is usually difficult to pre-specify weights since the importance of each period is not easily understood and measured. More attractive, the sum of derived weights in our formulating approach is up to one, which makes sense of the magnitude comparison between the overall R&D efficiency score and period ones of each region. Compared with the Kao's (2013) modelling approach, this paper's approach can present a systemic measurement and decomposition for the overall efficiency score of multi-period input-output processes.

Although this study has elaborately designed the regional R&D efficiency model over multiple periods, there are some potential investigations in our empirical studies. In order to obtain more robust efficiency measurement, a feasible approach is to combine one statistical method (e.g., bootstrap method) (see Chen and Guan, 2012). For this purpose, another possible way is to apply the order-m efficiency analysis (Simar and Wilson, 2006) in our analytical framework, which is less sensitive to outliers and statistical noise in the data than deterministic non-parametric approaches (Cazals et al., 2002). Moreover, our model for multi-period efficiency measurement does not fully account for the time preference of period efficiency scores in the overall efficiency score in terms of time discounting although the present period is endogenously assigned more importance in it. Following Fukuyama and Weber (2015) and Fukuyama et al. (2016), a discount factor to account for time preference can be introduced to our model. Finally, our modeling approach is not subject to the structure of dynamic processes. This means that it can be extended to various situations, such as when intermediate outputs produced in one period are not used as inputs in the next period, and there are exogenous intermediate inputs or shared inputs among periods. A useful future study would be to extend our multi-period modeling approach to the innovation process with a multi-division operation structure such as Guan and Chen (2012).

Appendix:

A. Formulation of the input-oriented Kao-DDEA model

Kao (2013) extended the formulation approach of Kao and Hwang's (2010) relational network DEA model, and proposed an output-oriented formulation approach for the overall and period efficiency measures of the multi-period process in Figure 2. To facilitate the comparison with it in this paper, we propose the input-oriented version of Kao's (2013) relational dynamic DEA model, here named the Kao-DDEA model, for the whole overall efficiency, E_k, as follows:

$$E_k = \max \frac{\sum_{t=1}^{T}\sum_{r=1}^{s} u_r Y_{rk}^{(t)} + \sum_{p=1}^{q} w_p Z_{pk}^{(T+1)}}{\sum_{t=1}^{T}\sum_{i=1}^{m} v_i X_{ik}^{(t)} + \sum_{p=1}^{q} w_p Z_{pk}^{(1)}}$$

$$\begin{aligned} s.t.\ & \frac{\sum_{t=1}^{T}\sum_{r=1}^{s} u_r Y_{rj}^{(t)} + \sum_{p=1}^{q} w_p Z_{pj}^{(T+1)}}{\sum_{t=1}^{T}\sum_{i=1}^{m} v_i X_{ij}^{(t)} + \sum_{p=1}^{q} w_p Z_{pj}^{(1)}} \le 1,\ j = 1,2,\cdots,n \\ & \frac{\sum_{r=1}^{s} u_r Y_{rj}^{(t)} + \sum_{p=1}^{q} w_p Z_{pj}^{(t+1)}}{\sum_{i=1}^{m} v_i X_{ij}^{(t)} + \sum_{p=1}^{q} w_p Z_{pj}^{(t)}} \le 1,\quad t = 1,2,\cdots,T;\ \ j = 1,2,\cdots,n \\ & u_r, v_i, w_p \ge \varepsilon. \end{aligned} \tag{A.1}$$

where u_r , v_i and w_p are virtual multipliers, and ε is a small non-Archimedean number.

Model (A.1) can be reduced to the equivalent linear program form for the calculation of overall efficiency with the optimal multipliers (u_r^*, v_i^*, w_p^*) in virtue of Charnes and Cooper's (1962) transformation. After the optimal multipliers are obtained, the overall efficiency E_k and the t^{th} period efficiency $E_k^{(t)}$ $(t = 1,2,\cdots,T)$ for the DMU_k under evaluation are calculated respectively by the following formulas (A.2) and (A.3).

$$E_k = \max \frac{\sum_{t=1}^{T}\sum_{r=1}^{s} u_r Y_{rk}^{(t)} + \sum_{p=1}^{q} w_p Z_{pk}^{(T+1)}}{\sum_{t=1}^{T}\sum_{i=1}^{m} v_i X_{ik}^{(t)} + \sum_{p=1}^{q} w_p Z_{pk}^{(1)}} \tag{A.2}$$

$$E_k^{(t)} = \frac{\sum_{r=1}^{s} u_r^* Y_{rk}^{(t)} + \sum_{p=1}^{q} w_p^* Z_{pk}^{(t+1)}}{\sum_{i=1}^{m} v_i^* X_{ik}^{(t)} + \sum_{p=1}^{q} w_p^* Z_{pk}^{(t)}},\quad t = 1,2,\cdots,T, \tag{A.3}$$

Based on Kao (2013), it is reduced that an equal relationship between E_k and $E_k^{(t)}$ $(t = 1,2,\cdots,T)$, i.e., $1 - E_k = \sum_{t=1}^{T} \omega_k^{(t)} \cdot (1 - E_k^{(t)})$ exists, where

$$\omega_k^{(t)} = \frac{\sum_{i=1}^{m} v_i^* X_{ik}^{(t)} + \sum_{p=1}^{q} w_p^* Z_{pk}^{(t)}}{\sum_{t=1}^{T}\sum_{i=1}^{m} v_i^* X_{ik}^{(t)} + \sum_{p=1}^{q} w_p^* Z_{pk}^{(1)}},\quad t = 1,2,\cdots,T. \tag{A.4}$$

It is derived that

$$\begin{aligned} \sum_{t=1}^{T} \omega_k^{(t)} &= \sum_{t=1}^{T} \frac{\sum_{i=1}^{m} v_i^* X_{ik}^{(t)} + \sum_{p=1}^{q} w_p^* Z_{pk}^{(t)}}{\sum_{t=1}^{T}\sum_{i=1}^{m} v_i^* X_{ik}^{(t)} + \sum_{p=1}^{q} w_p^* Z_{pk}^{(1)}} \\ &\ge \sum_{t=1}^{T} \frac{\sum_{i=1}^{m} v_i^* X_{ik}^{(t)} + \sum_{p=1}^{q} w_p^* Z_{pk}^{(t)}}{\sum_{t=1}^{T}\sum_{i=1}^{m} v_i^* X_{ik}^{(t)} + \sum_{t=1}^{T}\sum_{p=1}^{q} w_p^* Z_{pk}^{(t)}} \\ &= 1,\quad t = 1,2,\cdots,T. \end{aligned} \tag{A.5}$$

Only $\sum_{t=2}^{T}\sum_{p=1}^{q} w_p^* Z_{pk}^{(t)} = 0$ exists, the equal sign in the formula (A.5) exists. In fact, since $w_p^* > 0$

and $Z_{pk}^{(t)} > 0$ in practice, the equal situation usually in the formula (A.5) does not exist in the Kao-DDEA model. That is, the convex combination relationship between the overall efficiency score and period ones usually does not hold in the Kao-DDEA model, which brings some confusion and difficulty in performance comparison and management in practice. Here, it cannot be deduced that the overall efficiency is not less than the maximum period efficiency and more than the minimum period efficiency. In this situation, it is difficult to understand how the overall performance of dynamic system is resulted from the component performance of all periods together in the average sense.

B. Database and efficiency scores

B1. Descriptive statistics of indicators

Period	Full name of indicators		Role	Year	Average	St.Dev	Max.	Min.
2006	R&D capital stock	RD_CS	Carry-over indicator	2005	2126628	2400848	9916659	83788
	R&D personnel	RD_P	Input indicator	2006	51733	43462	168398	2610
	R&D expenditure	RD_E		2006	1000675	1096690	4190144	32334
	R&D capital stock	RD_CS	Carry-over indicator	2006	2635303	2959279	12182323	100251
	SCI papers	PAP	Output indicator	2006	2456	3152	15546	30
	Domestic granted patents	PAT		2006	7187	9842	43516	97
2007	R&D capital stock	RD_CS	Carry-over indicator	2006	2635303	2959279	12182323	100251
	R&D personnel	RD_P	Input indicator	2007	59761	52829	199464	2915
	R&D expenditure	RD_E		2007	1180368	1283458	4666843	35176
	R&D capital stock	RD_CS	Carry-over indicator	2007	3240683	3605827	14545119	117547
	SCI papers	PAP	Output indicator	2007	2750	3399	16665	32
	Domestic granted patents	PAT		2007	9770	13466	56451	222
2008	R&D capital stock	RD_CS	Carry-over indicator	2007	3240683	3605827	14545119	117547
	R&D personnel	RD_P	Input indicator	2008	67922	62031	238684	3759
	R&D expenditure	RD_E		2008	1387055	1480806	5065618	34089
	R&D capital stock	RD_CS	Carry-over indicator	2008	3934948	4340721	17030194	135091
	SCI papers	PAP	Output indicator	2008	3021	3658	17805	37
	Domestic granted patents	PAT		2008	11727	16156	62031	295
2009	R&D capital stock	RD_CS	Carry-over indicator	2008	3934948	4340721	17030194	135091
	R&D personnel	RD_P	Input indicator	2009	78726	74561	283650	4603
	R&D expenditure	RD_E		2009	1749727	1810124	6164742	66691
	R&D capital stock	RD_CS	Carry-over indicator	2009	4731761	5148696	19274775	148916
	SCI papers	PAP	Output indicator	2009	3291	3920	18945	42
	Domestic granted patents	PAT		2009	16636	24838	87286	368
2010	R&D capital stock	RD_CS	Carry-over indicator	2009	4731761	5148696	19274775	148916
	R&D personnel	RD_P	Input indicator	2010	88089	87084	344692	4858
	R&D expenditure	RD_E		2010	2068103	2167366	7294408	84544
	R&D capital stock	RD_CS	Carry-over indicator	2010	5771724	6170794	22255695	193269
	SCI papers	PAP	Output indicator	2010	3750	4385	20868	44
	Domestic granted patents	PAT		2010	24778	36906	138382	264

B2. Efficiency scores respectively by our model, CCR and Kao-DDEA model

Provinces	Efficiency scores												Weights					
	CCR						Kao-DDEA						Kao-DDEA					
	Overall	2006	2007	2008	2009	2010	Overall	2006	2007	2008	2009	2010	2006	2007	2008	2009	2010	Sum
Beijing	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9030	0.9896	0.9797	0.9865	0.9500	0.9640	0.4776	0.5752	0.668	0.7849	0.8934	3.3991
Tianjin	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9229	0.9677	0.9933	0.9623	0.9883	0.9671	0.3821	0.4755	0.6057	0.7358	0.9172	3.1163
Hebei	0.9902	0.9859	0.9992	0.9929	0.9799	0.9934	0.8944	0.9551	0.9880	0.9696	0.9473	0.9743	0.4017	0.4953	0.6166	0.7573	0.8946	3.1655
Shanxi	0.9743	0.9448	0.9636	0.9865	0.9764	1.0000	0.8823	0.9268	0.9469	0.9663	0.9444	0.9928	0.3758	0.4602	0.5695	0.7249	0.8711	3.0014
I.Mongolia	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.8869	0.9438	0.9443	0.9607	0.9103	1.0000	0.2622	0.3526	0.472	0.6707	0.8685	2.6260
Liaoning	0.9931	1.0000	1.0000	0.9921	0.9944	0.9790	0.8752	0.9822	0.9596	0.9712	0.9464	0.9605	0.4652	0.559	0.6457	0.7595	0.8754	3.3047
Jilin	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9107	0.9548	0.9273	0.9650	0.8877	0.8713	0.1649	0.1931	0.2000	0.2344	0.2677	1.0600
Heilongjiang	0.9872	1.0000	0.9853	0.9768	0.9759	0.9980	0.8966	0.9855	0.9832	0.9486	0.9455	0.9816	0.4028	0.5000	0.6194	0.7508	0.8878	3.1608
Shanghai	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9588	0.9806	0.9984	0.999	0.9667	0.9917	0.4228	0.5107	0.6112	0.7367	0.8483	3.1299
Jiangsu	0.9921	0.9788	0.9896	1.0000	0.9921	1.0000	0.9367	0.9594	0.9801	0.9637	0.9816	0.9958	0.3817	0.4696	0.5892	0.728	0.8944	3.0628
Zhejiang	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9874	0.9678	1.0000	0.9980	1.0000	0.9993	0.3403	0.4316	0.5488	0.6826	0.8368	2.8402
Anhui	0.9866	0.9843	0.9853	0.9885	0.9748	1.0000	0.8993	0.9597	0.9803	0.9439	0.9375	0.9966	0.3630	0.4407	0.5547	0.6934	0.8426	2.8943
Fujian	0.9745	0.9731	0.9822	0.9835	0.9580	0.9758	0.8797	0.9589	0.9737	0.9654	0.9383	0.9702	0.4023	0.4848	0.5878	0.7247	0.8706	3.0702
Jiangxi	0.9889	0.9796	0.9821	0.9937	0.9913	0.9979	0.8946	0.9475	0.9639	0.9620	0.9617	0.9792	0.3700	0.4654	0.5885	0.7359	0.8957	3.0554
Shandong	0.9958	1.0000	0.9792	1.0000	1.0000	1.0000	0.9220	0.9834	0.9640	0.9548	0.9858	0.9789	0.3591	0.4583	0.5804	0.7163	0.9058	3.0198
Henan	0.9828	0.9693	0.9984	0.9966	0.9593	0.9903	0.8960	0.9319	0.9804	0.9873	0.9248	0.9878	0.3472	0.4332	0.549	0.7217	0.8769	2.9280
Hubei	0.9899	0.9884	0.9891	0.9975	0.9746	1.0000	0.8973	0.9607	0.9847	0.9550	0.9297	0.9898	0.3582	0.4391	0.5487	0.6919	0.841	2.8789
Hunan	0.9898	1.0000	0.9488	1.0000	1.0000	1.0000	0.8976	0.9658	0.9436	0.9300	0.9520	1.0000	0.3327	0.4116	0.5168	0.6584	0.8344	2.7538
Guangdong	0.9901	1.0000	1.0000	0.9903	0.9690	0.9911	0.9124	0.9609	0.9693	0.9763	0.9544	0.9848	0.3809	0.4648	0.5652	0.7036	0.8511	2.9656
Guangxi	0.9726	0.9734	0.9802	0.9605	0.9751	0.9738	0.8600	0.9616	0.9772	0.9271	0.9271	0.9661	0.3441	0.4186	0.5331	0.6756	0.8607	2.8321
Chongqing	0.9852	1.0000	0.9715	0.9828	0.9716	1.0000	0.9069	0.9956	0.9683	0.9689	0.9465	0.9777	0.3757	0.4736	0.5799	0.7239	0.8833	3.0364
Sichuan	0.9797	0.9889	0.9646	0.9935	0.9627	0.9888	0.8710	0.9661	0.9423	0.9723	0.9348	0.9772	0.4387	0.5263	0.6050	0.7308	0.8485	3.1493
Guizhou	0.9826	1.0000	1.0000	0.9628	0.9500	1.0000	0.8993	0.9916	0.9899	0.9393	0.9279	0.9971	0.4107	0.4960	0.6063	0.7345	0.8627	3.1101
Yunan	0.9888	0.9890	0.9811	0.9974	0.9895	0.9869	0.9074	0.9692	0.9774	0.9806	0.9588	0.9711	0.4012	0.5006	0.6146	0.7546	0.8979	3.1689
Shaanxi	0.9892	0.9947	1.0000	0.9851	0.9687	0.9973	0.8653	0.9700	0.9522	0.9593	0.9317	0.9792	0.4640	0.5501	0.6329	0.7473	0.8507	3.2449
Gansu	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9763	0.9177	1.0000	0.9843	0.9712	1.0000	0.1691	0.1817	0.2047	0.2301	0.2452	1.0307
Qinghai	0.9640	0.9842	1.0000	1.0000	0.8711	0.9647	0.8106	0.9640	0.9660	0.9792	0.8472	0.9579	0.4251	0.4994	0.5669	0.7233	0.8261	3.0408
Ningxia	0.9789	0.9088	0.9861	1.0000	0.9997	1.0000	0.9092	0.8844	0.9476	0.9986	0.9782	0.9921	0.3729	0.4544	0.572	0.7338	0.8877	3.0208
Xinjiang	0.9883	1.0000	1.0000	0.9501	0.9938	0.9977	0.8887	0.9490	0.9876	0.9150	0.9488	0.9930	0.3658	0.4289	0.5488	0.6782	0.8511	2.8728

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References:

Bai, J.H., 2013. On Regional Innovation Efficiency: Evidence from panel data of China's different provinces. Regional Studies, 47(5), 773-788.

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science, 30(9), 1078-1092.

Berlemann, M., Wesselhöft, J.E., 2014. Estimating aggregate capital stocks using the perpetual inventory method. Review of Economics, 65(1), 1-34.

Bonaccorsi, A., Daraio, C., 2003. A robust nonparametric approach to the analysis of scientific productivity. Research Evaluation, 12(1), 47-69.

Briec, W., Kerstens, K., 2009. Multi-horizon Markowitz portfolio performance appraisals: a general approach. Omega, 37(1), 50-62.

Broekel, T., 2012. Collaboration intensity and regional innovation efficiency in Germany - A conditional efficiency approach. Industry and Innovation, 19(2), 155-179.

Broekel, T., 2015. Do cooperative research and development (R&D) subsidies stimulate regional innovation efficiency? Evidence from Germany. Regional Studies, 49(7), 1087-1110.

Cao, C., Li, N., Li, X., Liu, L., 2013. Reforming China's S&T system. Science, 341(6145), 460-462.

Cazals, C., Florens, J.P., Simar, L., 2002. Nonparametric frontier estimation: a robust approach, Journal of Econometrics, 106(1), 1-25.

Charnes, A., Cooper, W.W., 1962. Programming with linear fractional functionals. Naval Research Logistics Quarterly, 9(3-4), 181-196.

Charnes, A., Cooper, W.W., Rhodes, L., 1978. Measuring the efficiency of decision making units. European Journal of Operational Research, 2(4), 429-444.

Chen, C.-M., van Dalen, J., 2010. Measuring efficiency in dynamic production: theories and an integrated methodology. European Journal of Operational Research, 203(3), 749-760.

Chen, K.H., Guan, J.C., 2011. Mapping the innovation production process from accumulative advantage to economic outcomes: A path modeling approach. Technovation, 31(7), 336-346.

Chen, K.H., Guan, J.C., 2012. Measuring China's regional innovation systems: Application of network data envelopment analysis (DEA). Regional Studies, 46(3), 355-377.

Chen, K.H., Kou, M.T., 2014. Staged efficiency and its determinants of regional innovation systems: a two-step analytical procedure. The Annals of Regional Science, 52(2), 627-657.

Färe, R., Grosskopf, S., 1996. Intertemporal production frontiers: With dynamic DEA. Boston: Kluwer Academic Publishers.

Fritsch, M., Slavtchev, V., 2010. How does industry specialization affect the efficiency of regional innovation systems?. The Annals of Regional Science, 45(1), 87-108.

Fritsch, M., Slavtchev, V., 2011. Determinants of the efficiency of regional innovation systems. Regional Studies, 45(7), 905-918.

Fu, X., 2008. Foreign direct investment, absorptive capacity and regional innovation capabilities in China. Oxford Development Studies, 36(1), 89-110.

Fu, X., 2015. China's path to innovation. Cambridge University Press, Cambridge.

Fukuyama, H., Weber, W.L., Xia, Y., 2016. Time substitution and network effects with an application to nanobiotechnology policy for US universities. Omega, 60(1), 34-44.

Fukuyama, H., Weber, W.L., 2015. Measuring Japanese bank performance: a dynamic network DEA approach. Journal of Productivity Analysis, 44(3), 249-264.

Guo, B., 2008. Technology acquisition channels and industry performance: An industry-level analysis of Chinese large-and medium-size manufacturing enterprises. Research Policy, 37(2), 194-209.

Griliches, Z., 1979. Issues in assessing the contribution of R&D to productivity growth. Bell Journal of Economics, 10(1), 92-116.

Guan, J.C., Chen, K.H., 2010a. Modeling macro-R&D production frontier performance: an application to Chinese province-level R&D. Scientometrics, 82(1), 165-173.

Guan, J.C., Chen, K.H., 2010b. Measuring the innovation production process: a cross-region empirical study of China’s high tech innovations. Technovation, 30(5), 348-358.

Guan, J.C., Chen, K.H., 2012. Modeling the relative efficiency of national innovation systems. Research Policy, 41(1), 102-115.

Guellec, D., van Pottelsberghe de la Potterie, B., 2004. From R&D to productivity growth: do the institutional settings and the source of funds of R&D matter? Oxford Bulletin of Economics and Statistics, 66(3), 353-378.

Hall, B. H., Mairesse, J., 1995. Exploring the relationship between R&D and productivity in French manufacturing firms. Journal of econometrics, 65(1), 263-293.

Han, U., Asmild, M., Kunc, M., 2016. Regional R&D Efficiency in Korea from static and dynamic perspectives. Regional Studies, 50(7), 1170-1184.

Hu, A.G.Z., Jefferson, G.H., 2004. Returns to research and development in Chinese industry: evidence from state-owned enterprises in Beijing. China Economic Review, 15(1), 86-197.

Huang, N., 2007. Measuring the stock of the aggregate R&D capital in the growth accounting framework. Working Paper prepared for the CEA Annual Meeting, June 1st- June 3rd, 2007.

Kao, C., 2013. Dynamic data envelopment analysis: A relational analysis. European Journal of Operational Research, 227(2), 325-330.

Kao, C., Hwang, S.-N., 2010. Efficiency measurement for network systems: IT impact on firm performance. Decision Support Systems, 48(3), 437-446.

Kapelko, M., Oude Lansink, A., Stefanou, S.E., 2014. Assessing dynamic inefficiency of the Spanish construction sector pre- and post-financial crisis. European Journal of Operational Research, 237(1), 349-357.

Li, Q., 1996. Nonparametric testing of closeness between two unknown distribution functions. Econometric Reviews, 15(3), 261-274.

Li, X., 2009. China’s regional innovation capacity in transition: an empirical approach. Research Policy, 38(2), 338-357.

Li, Y., Chen, Y., Liang, L., Xie, J., 2012. DEA models for extended two-stage network structures. Omega, 40(5), 611-618.

Nemoto, J., Goto, M., 2003. Measurement of dynamic efficiency in production: an application of data envelopment analysis to Japanese electric utilities. Journal of Productivity Analysis, 19(2), 191-210.

OECD, 1994. The Measurement of scientific and technological activities: standard practice for surveys of research and experimental development (Frascati Manual). OECD Publishing, Paris.

OECD, 2008. OECD Reviews of Innovation Policy: China. OECD Publishing, Paris.

Pakes, A., Griliches, Z., 1984. Patents and R&D at the firm level: a first look. In: Z. Griliches (Ed.), R&D, Patents, and Productivity. University of Chicago Press, Chicago.

Runiewicz-Wardyn, M., 2013. The efficiency of regional innovation systems (RIS). The role of high-tech industry and knowledge-intensive services. In: Runiewicz-Wardyn, M. (Ed.). Knowledge flows, technological change and regional growth in the European Union, Springer International Publishing, pp. 81-102.

Scotchmer, S., 1991. Standing on the shoulders of giants: cumulative research and the patent law. Journal of Economic Perspectives, 5(1), 29-41.

Silva, E., Stefanou, S.E., 2007. Dynamic efficiency measurement: theory and application. American Journal of Agricultural Economics, 89(2), 398-419.

Silva, E., Oude Lansink, A., Stefanou, S.E., 2015. The adjustment-cost model of the firm: duality and productive efficiency. International Journal of Production Economics, 168, 245-256.

Simar, L., Wilson, P.W., 2006. Statistical inference in nonparametric frontier models: recent developments and perspectives, in Fried, H., Lovell, C.A.K., Schmidt, S. (Eds) The Measurement of Productive Efficiency and Productivity Change, Oxford University Press, New York, pp. 421-521.

Simar, L., Zelenyuk, V., 2006. On testing equality of distributions of technical efficiency scores. Econometric Reviews, 25(4), 497-522.

Tone, K., 2001. A slacks-based measure of efficiency in data envelopment analysis. European Journal of Operational Research, 130(3), 498-509.

Tone, K., Tsutsui, M., 2010. Dynamic DEA: a slacks-based measure approach. Omega, 38(3), 145-156.

Tone, K., Tsutsui, M., 2014. Dynamic DEA with network structure: A slacks-based measure approach. Omega, 42(1), 124-131.

Wang, N., Hagedoorn, J., 2014. The lag structure of the relationship between patenting and internal R&D revisited. Research Policy, 43(8), 1275-1285.

Yu, M.M., Chen, L.H., Hsiao, B., 2016. Dynamic performance assessment of bus transit with the multi-activity network structure. Omega, 60(4), 15-25.

Zabala-Iturriagagoitia, J.M., Voigt, P., Gutiérrez-Gracia, A., Jiménez-Sáez, F., 2007. Regional innovation systems: How to assess performance. Regional Studies, 41(5), 661-672.