PERFORMANCE EVALUATION OF THE CHINESE HIGH-TECH INDUSTRY: A TWO-STAGE DEA APPROACH WITH FEEDBACK AND SHARED RESOURCE

DAWEI WANG
School of Management
University of Science and Technology of China
Hefei, Anhui Province 230026, China

LINLIN ZHAO*
School of Business
Nanjing Audit University
Nanjing, Jiangsu Province 211815, China
Huishang Futures
Hefei, Anhui Province 340100, China

FENG YANG
School of Management
University of Science and Technology of China
Hefei, Anhui Province 230026, China

KEHONG CHEN
International Institute of Finance
School of Management
University of Science and Technology of China
Hefei, Anhui Province 230026, China

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ABSTRACT. The operational process of high-tech industry can be separated into a research and development stage (RDS) and a commercialization stage (CS). Within this, the research employees are shared by both stages, and part of the economic output of the CS becomes a feedback factor and continuously flows back to the RDS. Using this framework, this study establishes cooperative and non-cooperative two-stage data envelopment analysis (DEA) models to explore the efficiencies of regional high-tech industries in China. The proposed approach can calculate the overall efficiency and stage efficiencies simultaneously. Based on empirical data of high-tech industries in 29 regions of China from 2012 to 2016, it is concluded that (1) a harmony exists between the RDS and the CS in the cooperative case, while a disharmony happens between the RDS and CS in the non-cooperative case; (2) there exist distinct geographic characteristics regarding the stage inefficiencies of these regional high-tech industries.

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* Corresponding author: Linlin Zhao.
1. Introduction. Technological innovation has been increasingly recognized as an important source of economic growth. In China, since the national strategy of innovation-driven development was implemented, much effort has been devoted to promoting technological innovation. For example, China is the fastest-growing country in terms of the R&D expenditure in the world, with an annual growth rate of 11.1% from 2013 to 2016 (Chinese Statistical Yearbook, 2017). The high-tech industry, in particular, has become a priority for China. The Chinese government has established its “Chinese High-tech R&D(863) Program ” and “Made in China 2025 initiative” to promote the development of its high-tech industry. From 2016 to 2017, the gross industrial output value and export of China’s high-tech industry have grown at an annual rate of 10% and 25%, respectively. However, such growth was achieved at the expense of a large amount of human and financial resources (see [53]). To promote the sustainable development of China’s high-tech industry, the Chinese government has to measure the industry’s performance to identify strengths and weaknesses, which can provide information regarding the future improvement of operational activities (see [6, 38]).

![Figure 1. The operational process of Chinese high-tech industry](image-url)

To evaluate the operational performance of high-tech industries, it is necessary to obtain a comprehensive understanding of the operational process of this type of industry. The operational process of a high-tech industry can be separated into two stages: the research and development stage (RDS) and the commercialization stage (CS) \(^1\). In the RDS, the research employees and funds (e.g., government funds and self-raised fund by enterprises) are consumed to achieve patents. In the CS, the patents, research employees, and expenditures on new product development and technological innovation are used to achieve the economic outputs (e.g., the business income and sales revenue). Note that the research employees are shared by the two stages (i.e., a shared resource), and the patents are both an output of the first stage and an input of the second stage (i.e., an intermediate factor). In addition, part of the economic output in the CS (e.g., self-raised fund by enterprises) may be converted to input for the RDS to complement the government funding; that is, part of the CS output is fed back as input to the RDS. Since the research employees are shared resources, the patents are an intermediate factor, and part of the economic output becomes a feedback factor, these three factors significantly impact the operational performance of both stages.

\(^1\)For more similar literature (see [9, 52])
In addition, in some practical scenarios, the RDS (CS) possesses plentiful re-
resources and has a dominant advantage over the CS (RDS). From this perspective,
the RDS (CS) can be viewed as a leader and the CS (RDS) as a follower. In such
situations, the decision makers take the performance of the RDS (CS) as the
first-order objective, whereas the performance of the CS (RDS) is the second-order
objective. However, in other cases, the decision makers treat the RDS and the CS
equally. In the context of equality of stages, it is reasonable to view the two stages as
operating in a cooperative manner, so the decision makers intend to optimize both
stages’ efficiencies simultaneously. Therefore, the interactive relationship between
the RDS and the CS plays an important role in achieving sustainable operations
and affecting the performance of the stages and the high-tech industry operational
efficiency.

The impacts of the intermediate factors, shared resources, feedback factors, and
interactive relationship on the efficiencies of the two stages, as well as the whole
high-tech industry, raise the following important issues: (1) As a high-tech industry
is a multi-input and multi-output unit, an evaluation approach considering multiple
factors is required to correctly measure its operational performance. (2) In a high-
techn industry, it is critical to simultaneously estimate stage efficiencies as well as
overall efficiency. (3) How does the interactive relationship between the RDS and
the CS affect both the overall and stage efficiencies of a high-tech industry?

In the literature, data envelopment analysis (DEA) has been widely applied to
measure the performance of high-tech industry (see [2, 28]). Initiated by Charnes
et al. [5], DEA is a nonparametric approach for measuring the relative efficiency
of peer decision making units (DMUs) with multiple inputs and outputs (see [13]).
Because it provides useful information for sustainable operations, DEA has been
viewed as a powerful efficiency analysis tool in the high-tech industry (see [2, 18]).

To accurately measure the operational performance of Chinese high-tech indus-
try, this study proposes cooperative and non-cooperative two-stage DEA models by
considering intermediate factors, shared resources, and feedback factors. The main
contributions of this study to existing literature are summarized as follows. First,
this study is the first to simultaneously consider the effects of intermediate factors,
shared resources, feedback factors and interactive relationship on the operational
efficiencies of high-tech industries. To this end, non-cooperative and cooperative
models are proposed to better identify the interaction between the internal stages.
Second, in the described approach, the measures of overall efficiency and stage effi-
ciencies are also provided. With these efficiency measures, the decision makers can
identify the sources of operational inefficiencies in high-tech industries. Further-
more, the proposed approach is applied to measure the operational efficiencies of
regional high-tech industries in China, which provides useful information for deci-
sion makers to overcome the inefficiencies of the internal stages and to improve the
efficiencies of the regional high-tech industries in China.

The rest of the paper is organized as follows. Section 2 reviews the existing liter-
ature on assessment of technological innovation efficiency and network DEA related
research. Section 3 describes the notation and assumption and Section 4 introduces
the non-cooperative and cooperative two-stage DEA models with intermediate fac-
tor, shared resources and feedback factors. In Section 5, the proposed approach
is applied to evaluate the operational efficiencies of Chinese high-tech industries.
Conclusions are provided in Section 6.
2. Literature review.

2.1. Innovation efficiency assessment. Numerous studies have been performed to evaluate the efficiency of high-tech industry, which can be divided into two parts: black-box and network structure. The first stream of research applies traditional DEA approaches to evaluate the efficiency of high-tech industry, such as the performances of six high-tech industries in Taiwan’s Hsinchu Science Park (see [6]), semiconductor industry (see [35]) and high-tech manufacturing sectors in China(see [40]), the relationship between competitiveness and technological innovation capability (see [19]), the relationship between the industrial development environment and the innovation efficiency (see [32]), the effect of R&D investment on relative R&D efficiency (see [22]), influencing factors of the technological innovation efficiency (see [33]). All these studies treat the evaluated high-tech industries as a “black box” without considering the impacts of intermediate factors such as the patents, shared resources like research employees, and feedback factors like self-raised funds by the enterprises.

To better identify the sources of inefficiencies of high-tech industries, the second stream of the research treats the operational process as a network structure. Within such a framework, the overall efficiency of high-tech industry is decomposed into stage efficiencies. Guan and Chen [17] applied a relational network DEA model to evaluate the technological innovation efficiency of the high-tech industry in 26 regions of China. Wang et al. [44] proposed a two-stage innovation efficiency model to evaluate the efficiencies of 38 Chinese new energy enterprises. Deng et al. [14] used a network DEA approach considering undesirable outputs to estimate the green innovation efficiency in China’s high-tech manufacturing industry. Chen et al. [9] used a weighted additive network model with shared resources to estimate performance of China’s high-tech industry. Wang et al. [46] constructed two-stage network DEA model with shared inputs, additional intermediate inputs, and free intermediate outputs to empirically assess and decomposes the technological innovation efficiency of high-tech industries in China at the industrial level. Zhang et al. [52] employed a Russell multi-activity network DEA model to appraise the innovation performance of China’s high-tech industries, in which the overall innovation process consists of an upstream research and development process and a downstream commercialization process. An et al. [2] applied a dynamic network DEA approach to assess the relative efficiencies of Chinese high-tech industries. Yu et al. [50] also developed a newly dynamic network DEA model for the performance evaluation of R&D, commercialization, and overall innovation processes to measure dynamic innovation performance of China’s high-tech companies. Although these studies have described the high-tech industries’ internal structures such as intermediate factors and shared resources, few have considered feedback factors and the interactive relationship between the stages.

2.2. Network DEA related research. A large body of literature has studied DMUs that have a two-stage network structure with intermediate products existing between the two stages. Generally, previous studies on two-stage system can be classified broadly into four categories (see [21]): (i) independent two-stage DEA approach recommended by Wang et al. [44] and Seiford and Zhu [39], which does not consider the possible conflicts between the two stages; (ii) network DEA approach proposed by Fare and Grosskopf [15], which considers the connection between two
stages by treating intermediate measures as unknown decision variables in optimising the overall efficiency of the evaluated DMU; (iii) rational DEA approach suggested by Kao and Hwang [26] and Chen et al. [10], which assumes a multiplicative or additive relationship between the overall and divisional efficiencies; and (iv) game theoretic DEA approach proposed by Liang et al. [30], which considers the two stages as two players in a game. The game theoretic DEA approach is the focus of the current work.

According to system structure, these two-stage network structure models can be classified into three categories: (a) serial structure models, (b) parallel structure models and (c) mixed structure models. In parallel structure models, the individual stages operate similarly to each other (see [3, 4, 48]). In serial structure models, two or more internal stages are linked by intermediate measures. This category is the focus of the current work. More and more researchers are improving the traditional two-stage models by taking more complex structure into account. For example, Liang et al. [34] and Li et al. [31] proposed a two-stage DEA model that considers feedback variables. Zha and Liang [51] and Chen et al. [11] developed a two-stage DEA model taking shared inputs into account. However, few studies have considered additional intermediate factors, shared resources, and feedback factors simultaneously. For example, Wu et al. [47] established a modified two-stage DEA model which involves feedback factors and additional exogenous inputs, but did not take into account shared resources. Similarly, Chen et al. [9] constructed a new two-stage network DEA model that considered additional exogenous inputs and shared resources, but not feedback factors.

Considering the actual situation of the technological innovation process of high-tech industries in China, it has great significance to recognize the complex structure of inputs and outputs from different stages. However, there is a lack of such research. Therefore, we model a network structure that simultaneously considers shared resources, additional exogenous inputs, and feedback factors to develop the DEA methodology further.

2.3. Summary of literature. Most of researches analyze the high-tech industries’ efficiencies but only consider internal structures with intermediate factors and shared resources. None has sufficiently explored the issues of high-tech industry efficiency by simultaneously taking intermediate factors, shared resources, feedback factors, and interactive relationships into account. When a high-tech industry is estimated to be inefficient, it is difficult to identify the sources of inefficiency, which are caused by the internal operational stages or the effects of the interactive relationship between two stages. Therefore, this study proposes cooperative and non-cooperative two-stage DEA models which consider intermediate factors, shared resources, and feedback factors to accurately measure the operational performance of the Chinese high-tech industry.

3. Problem description. It is assumed that there are n independent DMUs, denoted by $DMU_j (j = 1, \ldots, n)$. The operational process of each DMU can be regarded as a two-stage process (i.e, research and development stage and commercialization stage), as shown in Fig.2.

For each DMU, Stage 1 consumes m shared resources $x_{ij} (i = 1, \ldots, m)$, P regular inputs $H_{pj} (p = 1, \ldots, P)$, and B feedback inputs $F_{bj} (b = 1, \ldots, B)$ to produce D intermediate outputs $z_{dj} (d = 1, \ldots, D)$; Stage 2 generates feedback outputs and G regular outputs $Y_{gj} (g = 1, \ldots, G)$ by utilizing the intermediate outputs, shared
Research and development stage (RDS)

Commercialization stage (CS)

\[
H_{pj} \rightarrow (1-\omega_{ij})x_{ij} \rightarrow z_{dj} \rightarrow R_{kj} \rightarrow y_{gj}
\]

Figure 2. Two-stage process of Chinese high-tech industry

resources and \( K \) regular inputs \( R_{kj} (k = 1, \ldots, K) \). Note that \( z_{dj} \) denote the links between the two stages, \( x_{ij} \) denote the shared resources between the two stages, and \( F_{bj} \) denote the feedback variables. Assume that the \( x_{ij} \) are divided into \((1-\omega_{ij})x_{ij}\) and \( \omega_{ij}x_{ij} (i = 1, \ldots, m; 0 \leq \omega_{ij} \leq 1)\) for each DMU \( j = 1, \ldots, n \), reflecting the portions of shared resources used by Stages 1 and 2, respectively. All \( \omega_{ij} (i = 1, \ldots, m; j = 1, \ldots, n) \) should be within a certain interval to guarantee that each stage will be allocated a minimum amount of shared resources (see [9, 10]).

In some practical scenarios, the RDS (CS) possesses plentiful resources and has a dominant advantage over the CS (RDS). From this perspective, the RDS (CS) is viewed as a leader and the CS (RDS) as a follower. For example, currently, the development of new technology is given priority in the western region of China, while commercialization is more important in the eastern region of China. In such a situation, the decision makers take the performance of the RDS (CS) as the first-order objective, whereas the performance of the CS (RDS) is the second-order objective.

However, in other cases, the decision makers treat the RDS and the CS equally. In such a context, it is reasonable to view the two stages as operating in a cooperative manner, so the decision makers attempt to optimize the two stages’ efficiencies simultaneously. Next, we propose several models to estimate the performance of the stages in non-cooperative and cooperative situations.

4. The proposed models.

4.1. Non-cooperative efficiency measures. We first characterize the interactive relationship between the RDS and the CS in the non-cooperative context.

4.1.1. RDS dominates the system. In this subsection, we treat the RDS as the leader, meaning its performance is the priority, and the CS as the follower, whose efficiency is calculated subject to the requirement that the RDS efficiency is optimized. To characterize the lower and upper bounds for the proportions of shared resources in evaluating the efficiency of the RDS, we assume that \( x_{ij} \) are divided into \((1-\omega_{ij})x_{ij}\) and \( \omega_{ij}x_{ij} (i = 1, \ldots, m)\) for each DMU \( j = 1, \ldots, n \), corresponding to the portions of shared resources used by the RDS and the CS. Thus, the efficiency of the RDS (the leader) for DMU \( 0 \) is measured under constant return scale (CRS)\(^2\) as follows:

\(^2\)First of all, the scale of the RDS and CS of regional high-tech industry are relatively steady and does not change greatly in the short term. In addition, the CRS assumption is convenient to explore the efficiencies of the two stages and the whole system in the non-cooperative and cooperative scenarios. Therefore, we choose the CRS assumption.
can be converted to the following linear programming form.

\[
\begin{align*}
\max E_{10} & = \frac{\sum_{d=1}^{D} \pi_d z_{d0}}{\sum_{i=1}^{m} v_i (1 - \omega_{i0}) x_{i0} + \sum_{p=1}^{P} \varphi_p H_{p0} + \sum_{b=1}^{B} \delta_b F_{b0}} \\
\text{s.t.} & \quad E_{1j} = \frac{\sum_{d=1}^{D} \pi_d z_{dj}}{\sum_{i=1}^{m} v_i (1 - \omega_{ij}) x_{ij} + \sum_{p=1}^{P} \varphi_p H_{pj} + \sum_{b=1}^{B} \delta_b F_{bj}} \leq 1, j = 1, \ldots, n \\
& \quad v_i \geq 0, i = 1, 2, \ldots, m; \quad \pi_d \geq 0, d = 1, 2, \ldots, D; \quad \varphi_p \geq 0, p = 1, 2, \ldots, P; \\
& \quad \delta_b \geq 0, b = 1, 2, \ldots, B; \\
& \quad L_i \leq \omega_{ij} \leq U_i, i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n.
\end{align*}
\]

Note that \(L_i\) and \(U_i\) are the lower and upper bounds for the shared resource \(x_{ij}\) \((i = 1, \ldots, m)\). These lower and upper bounds are usually given by the decision makers based on the assignment of the two stages (see [9, 47]).

Let \(T = \sum_{i=1}^{m} v_i (1 - \omega_{i0}) x_{i0} + \sum_{p=1}^{P} \eta_p H_{p0} + \sum_{b=1}^{B} \delta_b F_{b0}\), \(\pi'_d = \frac{T}{\varphi_p'}, \varphi'_p = \frac{\varphi_p}{\varphi_p'}\), \(\delta'_b = \frac{\delta_b}{\varphi_p'}\), \(v'_i = \frac{v_i}{\varphi_p'}\), and \(\xi_{ij} = \omega_{ij} v'_i\), model (1) which is a linear fractional programming model can be converted to the following linear programming form.

\[
\begin{align*}
\max \sum_{d=1}^{D} \pi'_d z_{d0} \\
\text{s.t.} & \quad \sum_{d=1}^{D} \pi'_d z_{dj} - \sum_{i=1}^{m} v'_i x_{ij} - \sum_{i=1}^{m} \xi_{ij} x_{ij} - \sum_{p=1}^{P} \varphi'_p H_{pj} - \sum_{b=1}^{B} \delta'_b F_{bj} \leq 0, j = 1, \ldots, n \\
& \quad \sum_{i=1}^{m} v'_i x_{i0} - \sum_{i=1}^{m} \xi_{i0} x_{i0} - \sum_{p=1}^{P} \varphi'_p H_{p0} - \sum_{b=1}^{B} \delta'_b F_{b0} = 1 \\
& \quad v'_i \geq 0, i = 1, 2, \ldots, m; \quad \pi'_d \geq 0, d = 1, 2, \ldots, D; \quad \varphi'_p \geq 0, p = 1, 2, \ldots, P; \\
& \quad \delta'_b \geq 0, b = 1, 2, \ldots, B; \\
& \quad L_i v'_i \leq \xi_{ij} \leq U_i v'_i, i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n.
\end{align*}
\]

Correspondingly, the efficiency of the CS for \(DMU_0\) is measured under CRS as follows.

\[
\begin{align*}
\max E_{20} & = \frac{\sum_{k=1}^{K} \eta_k R_{k0} + \sum_{g=1}^{G} u_g Y_{g0}}{\sum_{i=1}^{m} v_i (1 - \omega_{i0}) x_{i0} + \sum_{k=1}^{K} \eta_k R_{k0} + \sum_{d=1}^{D} \pi_d z_{d0}} \\
\text{s.t.} & \quad E_{10} = \frac{\sum_{d=1}^{D} \pi_d z_{d0}}{\sum_{i=1}^{m} v_i (1 - \omega_{i0}) x_{i0} + \sum_{p=1}^{P} \varphi_p H_{p0} + \sum_{b=1}^{B} \delta_b F_{b0}} \\
& \quad \sum_{d=1}^{D} \pi_d z_{d0}
\end{align*}
\]
Proof. For the proof of this theorem, see Appendix A.

Theorem 4.1. If the shared resources are freely allocated to either of the two stages, that is, \(0 \leq \omega_{ij} \leq 1\), then the leader stage is efficient.

Proof. For the proof of this theorem, see Appendix A.
4.1.2. CS dominates the system. Similar to the previous case, we can treat the CS as the leader whose performance is the priority. Like Wu et al. [49], we assume that $x_{ij}$ are divided into $\omega_{ij}x_{ij}$ and $(1 - \omega_{ij})x_{ij}$ ($i = 1, \ldots, m$) used by stages 1 and 2 respectively. Then, the efficiency of the CS (the leader) for $DMU_0$ is measured under CRS as follows:

$$\max \sum_{b=1}^{B} \delta_b F_{b0} + \sum_{g=1}^{G} u_g' Y_{g0}$$

s.t.

$$\sum_{b=1}^{B} \delta_b' F_{b} + \sum_{g=1}^{G} u_g' Y_{gj} - \sum_{i=1}^{m} v_i' x_{ij} + \sum_{i=1}^{m} \xi_{ij} x_{ij} - \sum_{k=1}^{K} \eta_k' R_{kj}$$

$$- \sum_{d=1}^{D} \pi_d z_{dij} \leq 0, j = 1, \ldots, n$$

$$\sum_{i=1}^{m} v_i' x_{i0} + \sum_{i=1}^{m} \xi_{i0} x_{i0} - \sum_{k=1}^{K} \eta_k' R_{k0} - \sum_{d=1}^{D} \pi_d z_{d0} = 1$$

$$v_i' \geq 0, i = 1, 2, \ldots, m; \; \pi_d' \geq 0, d = 1, 2, \ldots, D; \; \delta_b' \geq 0, b = 1, 2, \ldots, B;$$

$$\eta_k \geq 0, k = 1, 2, \ldots, K; \; u_g \geq 0, g = 1, 2, \ldots, G;$$

$$v_i' - U_i v_i' \leq \xi_{ij} \leq v_i' - L_i v_i', i = 1, 2, \ldots, m; \; j = 1, 2, \ldots, n.$$  

(5)

Similar to model (4), the efficiency of the RDS for $DMU_0$ is measured by the following model:

$$\max \sum_{d=1}^{D} \pi_d'' z_{d0}$$

s.t.

$$\sum_{b=1}^{B} \delta_b'' F_{b0} + \sum_{g=1}^{G} u_g'' Y_{g0} - E_{20}^{2*}(\sum_{i=1}^{m} v_i'' x_{i0} - \sum_{i=1}^{m} \xi_{i0} x_{i0})$$

$$+ \sum_{k=1}^{K} \eta_k'' R_{k0} + \sum_{d=1}^{D} \pi_d'' z_{d0}) = 0$$

$$\sum_{d=1}^{D} \pi_d'' z_{dij} - \sum_{i=1}^{m} \xi_{ij} x_{ij} - \sum_{p=1}^{P} \varphi_p' H_{pj} - \sum_{b=1}^{B} \delta_b'' F_{b0}) \leq 0, j = 1, \ldots, n$$

$$\sum_{b=1}^{B} \delta_b'' F_{b} + \sum_{g=1}^{G} u_g'' Y_{gj} - \sum_{i=1}^{m} v_i'' x_{ij} + \sum_{i=1}^{m} \xi_{ij} x_{ij}$$

$$- \sum_{k=1}^{K} \eta_k'' R_{kj} - \sum_{d=1}^{D} \pi_d'' z_{dij} \leq 0, j = 1, \ldots, n$$

$$\sum_{i=1}^{m} \xi_{i0} x_{i0} + \sum_{p=1}^{P} \varphi_p'' H_{p0} + \sum_{b=1}^{B} \delta_b'' F_{b0} = 1$$

$$v_i'' \geq 0, i = 1, 2, \ldots, m; \; \pi_d'' \geq 0, d = 1, 2, \ldots, D; \; \varphi_p'' \geq 0, p = 1, 2, \ldots, P;$$

(6)
\[
\begin{align*}
\delta_k'' & \geq 0, k = 1, 2, \ldots, B; \quad \eta_k'' \geq 0, k = 1, 2, \ldots, K; \quad \theta_g'' \geq 0, g = 1, 2, \ldots, G; \\
v_i'' - U_i v_i'' \leq \xi_{ij} \leq v_i'' - L_i v_i'', \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n.
\end{align*}
\]

4.2. Cooperative efficiency measures. In the previous subsection, we examine the non-cooperative efficiencies of the two stages, and thus, we can identify the inefficiencies of the stages easily. In this subsection, we explore the performance of the stages in a cooperative situation. This goal is triggered by the fact that the policymakers have the incentive to highlight the coordination between the RDS and the CS. With such a background, the RDS should interact with the CS cooperatively, and the objective of the DMU is to maximize the efficiencies of both stages simultaneously. The overall efficiency is defined as a weighted sum of the efficiency scores of Stages 1 and 2 and is formulated as follows:

\[
\begin{align*}
\max E_{0}^{c} &= \theta_1 E_{10} + \theta_2 E_{20} \\
\text{s.t.} & \sum_{d=1}^{D} \omega_d z_{d} & \leq 1, j = 1, \ldots, n \\
E_{1j} &= \frac{\sum_{b=1}^{B} \delta_b F_{bj} + \sum_{g=1}^{G} u_g Y_{gj}}{\sum_{i=1}^{m} v_i (1 - \omega_{ij}) x_{ij} + \sum_{p=1}^{P} \varphi_p H_{pj} + \sum_{b=1}^{B} \delta_b F_{bj}} \leq 1, j = 1, \ldots, n \\
E_{2j} &= \frac{\sum_{b=1}^{B} \delta_b F_{bj} + \sum_{g=1}^{G} u_g Y_{gj}}{\sum_{i=1}^{m} v_i (1 - \omega_{ij}) x_{ij} + \sum_{k=1}^{K} \eta_k R_{kj} + \sum_{d=1}^{D} \delta_d z_{dj}} \leq 1, j = 1, \ldots, n
\end{align*}
\]

Model (7) is a nonlinear fractional programming model. Let \( T_2 = \sum_{i=1}^{m} v_i (1 - \omega_{i0}) x_{i0} + \sum_{p=1}^{P} \varphi_p H_{p0} + \sum_{b=1}^{B} \delta_b F_{b0} \), \( T_3 = \sum_{i=1}^{m} v_i (1 - \omega_{i0}) x_{i0} + \sum_{k=1}^{K} \eta_k R_{k0} + \sum_{d=1}^{D} \delta_d z_{d0} \), \( \pi_d = \frac{\pi_d''}{T_2} \), \( \varphi_p = \frac{\varphi_p''}{T_2} \), \( \delta_b = \frac{\delta_b''}{T_2} \), \( v_i = \frac{v_i''}{T_2} \), \( u_g = \frac{u_g''}{T_2} \), \( \eta_k = \frac{\eta_k''}{T_2} \), \( \delta_d = \frac{\delta_d''}{T_2} \), \( t_0 = \frac{t_0''}{T_2} \), \( t_1 = \frac{t_1''}{T_2} \), \( t_2 = \frac{t_2''}{T_2} \).
The solution of the following nonlinear programming model:

\[ \xi_{ij} = \frac{v_i}{T_j}, \quad \xi'_{ij} = \frac{v_i}{T_j^*} = t \xi_{ij} \quad \text{and} \quad t = \frac{T_j^*}{T_j} \].

Then, model (7) can be transformed into the following nonlinear programming model:

\[
\begin{align*}
\max & \quad \theta_1 \sum_{d=1}^{D} \pi_d z_{d0} + \theta_2 \left( t \sum_{b=1}^{B} \delta_b F_{b0} + \sum_{g=1}^{G} u'_g Y_{g0} \right) \\
\text{s.t.} & \\
& \sum_{d=1}^{D} \pi_d z_{d0} - \sum_{i=1}^{m} v'_i x_{ij} + \sum_{i=1}^{m} \xi_{ij} x_{ij} - \sum_{p=1}^{P} \varphi'_p H_{pj} - \sum_{b=1}^{B} \delta_b' F_{b0} \leq 0, \quad j = 1, \ldots, n \\
& t \sum_{b=1}^{B} \delta_b' F_{b0} + \sum_{g=1}^{G} u'_g Y_{g0} - t \sum_{i=1}^{m} \xi_{ij} x_{ij} - \sum_{k=1}^{K} \eta_k R_{kj} - t \sum_{d=1}^{D} \pi_d z_{d0} \leq 0, \quad j = 1, \ldots, n \\
& \sum_{i=1}^{m} v'_i x_{i0} - \sum_{i=1}^{m} \xi_{i0} x_{i0} + \sum_{p=1}^{P} \varphi'_p H_{p0} + \sum_{b=1}^{B} \delta_b' F_{b0} = 1 \\
& t \sum_{i=1}^{m} \xi_{i0} x_{i0} + \sum_{k=1}^{K} \eta_k R_{k0} + t \sum_{d=1}^{D} \pi_d z_{d0} = 1 \\
& v'_i \geq 0, \quad i = 1, 2, \ldots, m; \quad \pi_d \geq 0, \quad d = 1, 2, \ldots, D; \quad \varphi'_p \geq 0, \quad p = 1, 2, \ldots, P; \\
& \delta_b \geq 0, \quad b = 1, 2, \ldots, B; \quad \eta_k \geq 0, \quad k = 1, 2, \ldots, K; \quad u'_g \geq 0, \quad g = 1, 2, \ldots, G; \\
& L_i v'_i \leq \xi_{ij} \leq U_i v'_i, \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n.
\end{align*}
\]

Note that model (8) is nonlinear but can be converted to a parametric linear programming model. From the constraint \( t \sum_{i=1}^{m} \xi_{i0} x_{i0} + \sum_{k=1}^{K} \eta_k R_{k0} + t \sum_{d=1}^{D} \pi_d z_{d0} = 1 \), we have \( t \sum_{d=1}^{D} \pi_d z_{d0} \leq 1 \). Let \( e^L_0 (e^U_0) \) denote the lower (upper) bound on the efficiency of the RDS when the RDS is dominated by (dominates) the CS. Then \( e^L_0 \leq \sum_{d=1}^{D} \pi_d z_{d0} \leq e^U_0 \) and the feasible extent of \( t \) can be specified as \( 0 \leq t \leq \frac{1}{e^L_0} \). The solution of \( e^L_0 \) is \( E^L_{10} \).

Noted that if the proposed model (8) has unique optimal solutions, the overall efficiency and stage efficiencies can be obtained directly. 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[42].

5. **Empirical study.** In this section, the appropriateness of the proposed approach is illustrated. Considering the availability of the data, this study uses the data of 29 regions (including provinces, autonomous regions and municipalities) in China (2012-2016) and evaluates the efficiencies of high-tech industries in these regions.

5.1. **Regions, variables and the data.** In mainland China, there are 31 regions (provinces, autonomous regions, and municipalities), which can be divided into four major areas: the eastern, central, western, and northeastern areas (National Bureau of Statistics of China, 2011). The eastern area is composed of seven coastal provinces (Hebei, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan)
and three municipalities (Beijing, Tianjin, and Shanghai). The central area has six inland provinces (Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan). The western area includes a municipality (Chongqing) and eleven provinces (Guangxi, Inner Mongolia, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, and Tibet). The northeast area has three provinces (Liaoning, Jilin, and Heilongjiang). Since sufficient data for Qinghai and Tibet are not available, they are excluded, and 29 regions are considered in this study.

As defined by OECD, high-tech industries are industries with R&D funding intensity significantly higher than other industries. According to the high-tech manufacturing industry (2017), Chinese high-tech industries include Pharmaceutical Manufacturing, Aircraft and Spacecraft Equipment Manufacturing, Electronic and Communication Equipment Manufacturing, Computer and Office Equipment Manufacturing, Medical Equipment and Instrument Manufacturing, and Photographic Equipment Manufacturing. In this study, we focus on the innovation process of Chinese high-tech industry which can be considered as same for all high-tech sectors (see [9, 17, 52]).

The input and output variables are defined as follows. As shown in Fig. 1, the RDS inputs are full-time equivalent, government funds, and self-raised fund by enterprises, and the output is the number of patents in force. Note that full-time equivalent is the shared input, and self-raised funds is a feedback variable. In the CS, the inputs are the number of patents in force, full-time equivalent, expenditure on new product development, and expenditure for technical renovation; and the outputs are self-raised funds, sales revenue of new products, and main business income.

The data is sourced from the China Statistics Yearbook on High Technology Industry (2013-2017). The descriptive statistics for the dataset are provided in Table 1.

The mean and standard deviation of the variables increases by years. The increase in the mean of the inputs indicates that as the government pays more attention to the high-tech industries, the invested resources increase as well. Consequently, the mean of the outputs increases as a result of the increased inputs. The standard deviations of the inputs are relatively large, which may be caused by

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3The following is the all data used in this research: [http://dx.doi.org/10.17632/y36z26262n](http://dx.doi.org/10.17632/y36z26262n).
unbalance in regional economies, diversity in regional development strategies, and differences in industrial structure. The standard deviations of most of the inputs increases, representing a growing disparity in resource investment by the regions. The large standard deviation of the outputs can also be regarded as the result of the difference in inputs.

Since the commercialization and patent application processes require a long time to complete (see [8]), the time lag is a factor to consider in measuring the operational efficiency of the high-tech industry. However, there is no time lag which is widely accepted as a standard in high-tech industry analysis (see [16]). Also, empirical results show that the time lag may have no significant impact on the measurement (see [38]). Hollanders and celikel-esser [23] empirically show that there is little effect of time lag on the performance of high-tech industry. For these reasons, we omit the effect of time lag in this study.

5.2. Empirical results. Based on the proposed models in this study, we calculate the efficiencies of regional high-tech industries in China from 2012 to 2016 in turn. Then, we calculate the average values of the five-year efficiencies. For the shared inputs, we consider the upper and lower bounds of the weights as 0.2 and 0.8, respectively. This is also a balance of the inputs consumed in various periods, which is consistent with the practice and the literature (see [9]). In the cooperative setting, it is assumed that both the RDS and CS have the same contribution to the high-tech industry’s overall efficiency, so the weights given to the two stages are the same: \( \theta_1 = \theta_2 = 0.5 \).

In this study, firstly, we compare the results of the two-stage approach described in this paper with those of the traditional black box model, which only considers the initial inputs and final outputs without considering the inner structure and the relationship between the stages. Then we analyze the efficiencies of regional high-tech industries in China using the proposed model.

Table 2 reports the average efficiencies of the RDS, the CS, and the overall system during 2012-2016 for the different scenarios.

In Table 2, the third and the fifth columns report the cooperative efficiencies of the two stages and the overall system. The sixth to ninth columns describe the non-cooperative efficiencies of the two stages and the overall system. The last column shows the values of efficiency evaluation by traditional black box model.

Table 2 shows the results of the traditional black box model indicates that both Tianjin and Chongqing were is measured as overall efficient throughout 2012-2016; however, the proposed model only found Tianjin to be overall efficient. As the proposed models fully consider the internal structure and are able to explore the detailed system efficiencies, the results are more scientific and closer to reality. Therefore, we can conclude that the proposed two-stage DEA models have stronger discriminating power with the introduction of shared resources, additional exogenous inputs and feedback factors compared with the traditional black box DEA model.

As shown in Table 2, in the cooperative case, the Chinese high-tech industry has similar average efficiency scores in the overall efficiency, RDS efficiency, and CS efficiency, i.e., 0.800, 0.839 and 0.754, respectively. This observation implies that the

\[ For \ more \ similar \ assumption \ (see \ [28]) \]

\[ The \ following \ is \ the \ detailed \ efficiencies \ of \ 29 \ provinces \ in \ China \ (2012-2016): \ https://data.mendeley.com/datasets/y6h8mskf2w/2. \]
RDS and the CS contribute equally to the inefficiency of the whole system. However, there exist great disparities among different regions. For example, Heilongjiang has relatively high efficiency in the CS (0.929) while it has a relatively low efficiency in the RDS (0.346), which means that the main inefficiency of Heilongjiang comes from the RDS. Shandong, Anhui, Hunan, and Yunnan are observed to be efficient in the RDS while inefficient in the CS. This observation indicates that efforts should be taken to improve the performance of their CS stages. Some regions (e.g., Guizhou, Gansu, and Ningxia) are estimated to be inefficient in both stages. This implies that to enhance the overall efficiency, these regions should take the efficiencies of both stages into consideration.

In the cooperative case, only Tianjin is measured as overall efficient throughout 2012-2016. This could be caused by the fact that this region has a large number of scientific and technological resources and creates a suitable environment for the development of innovation activities (Report on Regional Innovation Capability in China, 2012). Heilongjiang (0.637), Shaanxi (0.645), and Ningxia (0.657) have the lowest three overall efficiencies. Coincidently, the low efficiencies of these regions are all caused by the low RDS efficiencies. As for stage efficiency results, it is found that 13 regions are estimated as efficient in the RDS, while only one of the regions is measured as efficient in the CS. Shaanxi, Heilongjiang, and Hubei have the lowest efficiencies in the RDS, i.e., 0.314, 0.346, and 0.546, respectively.

Generally, the eastern area has a superior innovation environment, and the western area has a relatively inferior innovation environment. This means that the regions in the eastern area may have relatively high overall efficiencies, and the regions in the western area may have relatively low overall efficiencies. However, Table 2 shows that some regions in the eastern area, such as Hebei, Zhejiang, and Fujian, have relatively low overall efficiencies, while some regions in the western area, such as Chongqing, Guangxi and Inner Mongolia, have relatively high overall efficiencies. This observation suggests that the innovation environment may not be the only key factor which affects the innovation activities.

Note that only Tianjin is estimated as efficient in both the cooperative case and non-cooperative case. For most regions, there exists a disharmony between the RDS and CS in the non-cooperative case. For example, when the RDS is the leader, for most regions, the RDS is efficient while the CS has relatively low efficiency. This indicates that the inefficiencies of most regions are mainly caused by low efficiency in the CS. When the CS is the leader, all regions are estimated as efficient in the CS while having relatively low efficiencies in the RDS. This observation verifies the reasonability of Theorem 1, implying that the inefficiencies of regions are mainly caused by lower efficiencies in the RDS. Based on these results, we find that the two stages behave more consistently in the cooperative case than in the non-cooperative case. This finding can also be confirmed by Wilcoxon test results of the efficiency differences between the two stages, as shown in Table 3.

Table 3 shows that there exist significant efficiency differences between the two stages in the non-cooperative case, whereas significant efficiency differences do not exist between the two stages in the cooperative case. This phenomenon suggests that a harmony exists between the RDS and the CS in the cooperative case. In contrast, there exists a disharmony between the RDS and CS in the non-cooperative case. These findings indicate that to prompt the development of regional high-tech industries, the RDS and the CS should be treated equally in their operational processes.
Table 2. The average efficiencies of 29 regions in China (2012-2016).

| Area          | Cooperative model | Non-cooperative model | Traditional model |
|---------------|------------------|-----------------------|-------------------|
|               | Overall | RDS | CS | RDS | CS | RDS | CS | RDS | CS |
| Eastern area  |         | 0.957 | 1.000 | 0.913 | 1.000 | 0.896 | 1.000 | 0.866 | 1.000 | 0.887 |
| Beijing       |         | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Tianjin       |         | 0.693 | 0.630 | 0.756 | 0.960 | 0.356 | 0.336 | 1.000 | 0.369 |
| Hebei         |         | 0.945 | 1.000 | 0.890 | 1.000 | 0.860 | 1.000 | 0.814 | 1.000 | 0.840 |
| Shanghai      |         | 0.830 | 1.000 | 0.661 | 1.000 | 0.681 | 1.000 | 0.546 | 1.000 | 0.848 |
| Jiangsu       |         | 0.709 | 0.559 | 0.860 | 0.977 | 0.341 | 0.390 | 1.000 | 0.462 |
| Zhejiang      |         | 0.714 | 0.613 | 0.815 | 0.977 | 0.417 | 0.383 | 1.000 | 0.913 |
| Fujian        |         | 0.744 | 1.000 | 0.489 | 1.000 | 0.497 | 0.410 | 1.000 | 0.209 |
| Shandong      |         | 0.905 | 1.000 | 0.811 | 1.000 | 0.776 | 0.686 | 1.000 | 0.853 |
| Guangdong     |         | 0.753 | 0.999 | 0.502 | 1.000 | 0.502 | 0.289 | 1.000 | 0.850 |
| Hainan        |         | 0.852 | 0.995 | 0.710 | 0.995 | 0.709 | 0.561 | 1.000 | 0.355 |
| Central area  |         | 0.775 | 1.000 | 0.550 | 1.000 | 0.550 | 0.436 | 1.000 | 0.475 |
| Shanxi        |         | 0.804 | 0.870 | 0.738 | 0.946 | 0.654 | 0.385 | 1.000 | 0.552 |
| Anhui         |         | 0.832 | 0.743 | 0.922 | 0.655 | 0.923 | 0.571 | 1.000 | 0.775 |
| Jiangxi       |         | 0.725 | 0.546 | 0.904 | 1.000 | 0.372 | 0.402 | 1.000 | 0.485 |
| Hunan         |         | 0.772 | 1.000 | 0.544 | 0.919 | 0.560 | 0.426 | 1.000 | 0.968 |
| Northeastern  |         | 0.762 | 1.000 | 0.524 | 1.000 | 0.525 | 0.421 | 1.000 | 0.328 |
| Liaoning      |         | 0.906 | 1.000 | 0.812 | 1.000 | 0.812 | 0.700 | 1.000 | 0.556 |
| Heilongjiang  |         | 0.637 | 0.346 | 0.929 | 0.873 | 0.166 | 0.237 | 1.000 | 0.682 |
| Western area  |         | 0.880 | 0.709 | 0.849 | 0.995 | 0.709 | 0.561 | 1.000 | 0.957 |
| Inner Mongolia|         | 0.974 | 1.000 | 0.947 | 1.000 | 0.947 | 0.914 | 1.000 | 0.225 |
| Guangxi       |         | 0.978 | 0.991 | 0.964 | 0.930 | 0.977 | 0.874 | 1.000 | 0.060 |
| Chongqing     |         | 0.807 | 1.000 | 0.614 | 1.000 | 0.615 | 0.518 | 1.000 | 0.575 |
| Sichuan       |         | 0.658 | 0.700 | 0.617 | 0.995 | 0.259 | 0.196 | 1.000 | 0.250 |
| Guizhou       |         | 0.768 | 1.000 | 0.536 | 1.000 | 0.537 | 0.381 | 1.000 | 0.326 |
| Yunnan        |         | 0.645 | 0.314 | 0.976 | 0.932 | 0.171 | 0.244 | 1.000 | 0.216 |
| Shaanxi       |         | 0.735 | 0.768 | 0.701 | 1.000 | 0.431 | 0.388 | 1.000 | 0.428 |
| Qinghai       |         | 0.657 | 0.549 | 0.764 | 0.819 | 0.356 | 0.301 | 1.000 | 0.330 |
| Ningxia       |         | 0.778 | 0.999 | 0.558 | 1.000 | 0.558 | 0.455 | 1.000 | 0.497 |
| Xinjiang      |         | 0.809 | 0.839 | 0.754 | 0.965 | 0.592 | 0.565 | 1.000 | 0.593 |

Table 3. Wilcoxon test results of the efficiency differences between two stages*

| Efficiency comparisons | Cooperative model | RDS as the leader | CS as the leader |
|------------------------|-------------------|-------------------|------------------|
|                        | Statistic z (P-value) | Statistic z (P-value) | Statistic z (P-value) |
| RDS efficiency VS. CS  | 1.389 (0.165)INSIG | -4.441 (0.000)SIG  | -4.482 (0.000)SIG  |

* The significance level is 5%.

5.3. Regional analysis. In China, the levels of economic development significantly differ in the eastern, central, northeastern, and western areas. This difference has a nontrivial impact on the operational efficiencies of high-tech industries. In this subsection, we focus our attention on the efficiencies of the regions. Fig. 3 shows the average efficiencies of the whole system and two stages in the cooperative case. An analysis of Fig. 3 yields the following:

1) The overall efficiency of the whole country was stable during the period 2012-2016. Generally, the overall efficiency of the high-tech industry is closely related to the economic situation. The growth of the GDP in China experienced a relatively high speed (7.2%) in 2012-2016 (National Bureau of Statistics of China, 2017), which provides powerful economic support for innovation activities. At present, China has formed its own high-tech industrial system and initially has favorable conditions for accelerating the development of high-tech industries such as human resources, industrial base, technology reserves, market environment, and capital potential.
2) The eastern area has relatively high overall efficiency. Looking at annual average overall efficiencies, we find in Fig. 3(b) that the overall efficiency of the eastern area (0.825) is much larger than in the other areas. Coincidentally, the eastern area has the highest RDS efficiency and the highest CS efficiency. The central and western areas have the second-highest and third-highest overall efficiencies, and the northeastern area has the lowest overall efficiency. These rank results are consistent with the geographical characteristics of China’s high-tech industry. In 2015, the proportions of main business income of high-tech industry in eastern, central, western, and northeastern areas were 71.4%, 14.9%, 10.7%, and 3.06%, respectively (National Bureau of Statistics of China, 2016). These findings indicate that imbalanced development exists in these regional high-tech industries.

3) As for the annual average stage efficiencies, it can be seen in Fig. 3(b) that there exist significant differences between the RDS efficiency and the CS efficiency in the eastern and central areas. This observation suggests that the two stages behave inconsistently in the eastern and central areas, and the inefficiencies are primarily caused by low CS efficiencies. To improve the overall efficiencies, the eastern and central areas should focus their efforts on enhancing the CS efficiencies. In the northeastern and western areas, the efficiency differences between the two stages are small, and both stages are estimated as inefficient. This indicates that efforts should be exerted to improve the operational performance in both stages.

4) There exist significant disparities among the four areas in the RDS efficiencies, and the reverse happens in the CS efficiencies. This suggests that four areas behave inharmoniously in the RDS and behave harmoniously in the CS. This finding is consistent with the geographical characteristics of research and development activities in the Chinese high-tech industry. For example, in 2015, the eastern area had a relatively high R&D expenditure (78.2%), which is much larger than those of the central, western, and northeastern areas (accounted for 12.3%, 9.0% and 2.7%, respectively). Therefore, the eastern area performs better than other areas in the RDS.

Regarding the efficiencies of regional high-tech industries in the non-cooperative case, we analyze the results of average stage efficiencies in detail, as displayed in Figs. 4 and 5, as well as the results of annual stage efficiencies as depicted in Fig. 6.
As shown in Fig. 4(a) and Fig. 5(a) that the eastern area has the relatively high RDS efficiencies, whether the RDS is the leader or follower. Fig. 4(b) shows that when the RDS is the leader, the CS efficiencies of the eastern and central areas are higher than those of the whole country, whereas the reverse happens in the western and northeastern areas. Fig. 5(a) shows that when the CS acts as the leader, the RDS efficiencies of the eastern area are higher than those of the whole country, whereas the reverse happens in the other areas. Note that in Fig. 5(b), when
CS is the leader, all regions of the four areas are efficient in the CS, so the four areas are also efficient in the CS.

With regard to the annual average stage efficiencies, we find in Fig. 6 that there are significant efficiency differences between the RDS and CS in the non-cooperative case. For example, when the RDS as the leader, the RDS efficiencies of the four areas (i.e., 0.991, 0.919, 0.958, and 0.967, respectively) are much larger than those of the CS (i.e., 0.633, 0.628, 0.501 and 0.556, respectively). A similar phenomenon occurs when the CS is the leader. This finding verifies that there exists a disharmony between the RDS and CS in the non-cooperative case.

5.4. Discussion. As shown in Figs. 3-6, the eastern area has relatively high overall efficiency and stage efficiencies, so this area can be viewed as a benchmark for the other areas. This is consistent with the reality that the eastern region is the most developed area of China. It has comparative advantages, such as a sound industrial foundation, strong scientific and technological strength, abundant R&D personnel, plenty of R&D expenditure, support of the Chinese government, and geographical advantages. All these advantages provide a suitable environment for the development of high-tech industries.

On the contrary, the northeastern area has relatively low overall efficiency. The reasons are as follows. First, the industrial structure and layout are unreasonable, and the heavy industry has a dominant position. As a result, the growth of GDP in the northeastern area has declined in recent years. For example, its GDP growth is 1.1% in 2015, which is much lower than that of the whole country (6.91%). Therefore, there exist backward trends in policy support, technological innovation, and high-tech industry scale. For example, in 2015, the R&D expenditure of the northeastern area only accounted for 2.7% of the country’s total because it is very difficult to provide a suitable environment for the development of high-tech industries in this area. Second, there are problems of insufficient capacity for independent innovation, serious brain drain, inadequate market mechanisms, and the lack of a level playing field.

In Table 3, we see that there exist significant efficiency differences between the two stages in the non-cooperative case, whereas there do not exist significant efficiency differences between the two stages in the cooperative case. That is, a harmony exists between the RDS and the CS in the cooperative case. To promote the development of high-tech industries, the Chinese government should consider the coordination between the RDS and CS.

In addition, the economic environment may not be the only key factor which affects the innovation activities. The overall efficiencies of the regions in the western area are not necessarily low (e.g., Guangxi), whereas the overall efficiencies of the developed regions in the eastern area are not necessarily high (e.g., Fujian).

Based on the empirical results, we have the following policy implications for the sustainable development of Chinese high-tech industry.

1) Since the Chinese government has established “Made in China 2025” for promoting the development of the high-tech industry, the operational efficiency of this industry is receiving increasing attention. To improve the operational efficiency of the Chinese high-tech industry, it is recommended that the Chinese government establish incentive mechanisms to fully mobilize the initiative of the local governments for promoting innovation activities. In this study, the proposed approach can accurately classify the overall efficiency and stage efficiencies, and
thus can provide more information regarding the causes of inefficiencies of regional high-tech industries of China. Using this information, policymakers can determine an optimal strategy to improve the operational performance of the high-tech industry of China.

2) The overall efficiencies of the regional high-tech industries can be improved by having a high concern for the harmonious development of the RDS and CS, and for enhancing the efficiency of the CS. Table 3 shows that there exist significant efficiency differences between the two stages in the non-cooperative case, whereas no such differences exist in the cooperative case. Therefore, an urgent need is to continuously promote harmonious development between the RDS and CS. The eastern and central areas have the incentive to focus on the CS efficiencies and promote the transformation of high-tech achievements. The western and northeastern areas, however, are advised to enhance their capacities for independent innovation, increase their R&D expenditures, and optimize their industrial structures.

3) Three ways can substantively increase the overall efficiencies of China’s regional high-tech industries. First, the RDS is inconsistent with the CS in the non-cooperative case, so it is advisable to lower the inconsistency and increase the coordination of the two stages. Second, since the inefficiencies mainly originate from the CS, more efforts should be exerted to promote the transformation of high-tech achievements and increase the economic benefits of high-tech achievements. Third, there exist significant efficiency differences among the four areas, so to narrow such differences, the Chinese government should continuously implement the strategies of western development and revitalizing the northeast, and provide more policy support for development in those areas.

6. Conclusions. This study proposes cooperative and non-cooperative DEA models to evaluate the operational efficiencies of regional high-tech industries in China in 2012-2016. The operational process of regional high-tech industry is treated as a two-stage structure composed of a research and development stage and a commercialization stage. A distinct feature of a regional high-tech industry is the fact that research employees are shared resources, patents are an intermediate factor, and part of the economic output becomes a feedback factor. Based on the proposed approach, overall efficiency and stage efficiencies are obtained simultaneously. Since the proposed approach considers the effects of internal structure, shared resources, feedback factors, and the interactive relationship between the two stages, it can provide more information regarding the causes of inefficiencies in Chinese high-tech industries than previous DEA methods.

The proposed approach was applied to evaluate 29 regional high-tech industries in China. The major findings are summarized as follows. First, there exist significant efficiency differences between the two stages in the non-cooperative case but not in the cooperative case. That is, harmony is seen between the RDS and the CS in the cooperative case. In contrast, there exists disharmony between the RDS and CS in the non-cooperative case. To prompt the development of regional high-tech industries, the RDS and the CS should be treated equally and more effort should be taken to increase the coordination of the two stages. The balanced attention should be paid to the performance of the RDS and the CS from the systems perspective. The unilateral attention certainly causes many hazards to the whole system efficiency. Experiences show that neglecting indigenous performance of the RDS will
gradually lose core competence in international market, while neglecting commercial performance usually brings innovations to deviate market demand. Second, the Chinese high-tech industry is operated inefficiently regarding overall efficiency in 2012-2016, and the inefficiency came from both stages. However, there are great differences in inefficiencies for different regional high-tech industries. The inefficiencies of the eastern and central areas are caused by the CS, while the inefficiencies of the western and northeast areas come from both stages. In particular, the central area’s inefficiency is primarily the result of inefficient CS stages. Third, the overall efficiencies of regional high-tech industries show obvious geographical characteristics. The eastern area has a relatively high overall efficiency, followed in order by the central area and western areas, with the northeastern area having the lowest overall efficiency. These results are consistent with the known geographical characteristics of the development of the high-tech industry in China. Finally, the overall efficiency of the whole country was stable during the 2012-2016 period. This also verifies the effectiveness of the high-tech industry policies of the Chinese government.

In this study, we consider a static two-stage structure but the structure could be extended to a dynamic two-stage situation. The efficiency analysis was conducted from the perspective of the regional level. Further research may be conducted from the perspective of the firm level, which may provide helpful information for making specific industrial policies. In addition, we have only evaluated the efficiencies of regional high-tech industries in China over the years 2012-2016, and studying a longer period could also be a worthwhile extension to the current study. Moreover, the empirical results show that the economic environment may not be the only key factor which affects the innovation activities. Therefore, the economic environment factor should be a contextual variable to be analyzed in the future work. Finally, due to the innovation process is very complex within which many iterations and interventions take place, improvement of the model or evaluation criteria of regional high-tech industries should be potential research topics in future studies.

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Appendix A. Proof of Theorem 1

Proof. If $0 \leq \omega_{ij} \leq 1$, the corresponding dual formulation of model (2) is expressed as follow:

$$\begin{align*}
\min & \quad \theta \\
\text{s.t.} & \quad \sum_{j=1}^{n} \lambda_{j} H_{pj} \leq \theta H_{p0}, \forall p \\
& \quad \sum_{j=1}^{n} \lambda_{j} F_{bj} \leq \theta F_{b0}, \forall b \\
& \quad \sum_{j=1}^{n} \lambda_{j} z_{dj} \geq \theta z_{d0}, \forall d \\
& \quad \lambda_{j} x_{ij} + \rho_{ij} \geq 0, \forall i, j, j \neq 0
\end{align*}$$

(A.1)
\[
\lambda_0 x_{i0} - \theta x_{i0} + \rho_{i0} \geq 0, \forall i
\]
\[
\sum_{j=1}^{n} \lambda_j x_{ij} - \theta x_{i0} + \sum_{j=1}^{n} \rho_{ij} \leq 0, \forall i
\]
\[
\lambda_j \geq 0, \rho_{ij} \geq 0, i = 1, 2, ..., m; j = 1, 2, ..., n.
\]

From the constraints \( \lambda_j x_{ij} + \rho_{ij} \geq 0, \forall i,j, j \neq 0 \), we have \( \sum_{j=1, j \neq 0}^{n} \lambda_j x_{ij} + \sum_{j=1, j \neq 0}^{n} \rho_{ij} \geq 0 \). Meanwhile, the constraints \( \sum_{j=1}^{n} \lambda_j x_{ij} - \theta x_{i0} + \sum_{j=1}^{n} \rho_{ij} \leq 0, \forall i \) can be written as \( \sum_{j=1}^{n} \lambda_j x_{ij} - \theta x_{i0} + \sum_{j=1}^{n} \rho_{ij} = \sum_{j=1, j \neq 0}^{n} \lambda_j x_{ij} + \sum_{j=1, j \neq 0}^{n} \rho_{ij} + \lambda_0 x_{i0} + \rho_{i0} - \theta x_{i0} \leq 0 \), which means that \( \lambda_0 x_{i0} + \rho_{i0} - \theta x_{i0} \leq 0 \). Combined with \( \lambda_0 x_{i0} - \theta x_{i0} + \rho_{i0} \geq 0, \forall i \), we have \( \lambda_0 x_{i0} - \theta x_{i0} + \rho_{i0} = 0 \) and \( \sum_{j=1, j \neq 0}^{n} \lambda_j x_{ij} + \sum_{j=1, j \neq 0}^{n} \rho_{ij} \geq 0 \), which together indicate \( \lambda_j = 0, \rho_{ij} = 0, \forall i, j \neq 0 \). With the second constraint, we know \( \lambda_0 \geq 1 \).

At last, from the constraint \( \sum_{j=1}^{n} \lambda_j F_{bj} \leq \theta F_{b0}, \forall b, \theta_{\text{min}} = 1 \) can be obtained, which verifies that for \( 0 \leq \omega_{ij} \leq 1 \), the efficiency of the leader stage is efficient.

**Appendix B. Linear transformation steps for model 1.** Let \( T = \sum_{i=1}^{m} v_i (1 - \omega_{i0}) x_{i0} + \sum_{p=1}^{P} \eta_p H_{p0} + \sum_{b=1}^{B} \delta_b F_{b0} \), \( \pi' = \frac{\pi}{T}, \phi' = \frac{\phi}{T}, \delta'_b = \frac{\delta_b}{T}, v'_i = \frac{v_i}{T} \), and \( \xi_{ij} = \omega_{ij} v'_i \).

Objective function:

\[
E_{10} = \frac{\sum_{d=1}^{D} \pi_d z_{d0}}{T} = \sum_{d=1}^{D} \frac{\pi_d}{T} z_{d0} = \sum_{d=1}^{D} \pi'_d z_{d0}
\]

Constraint (B.1):

\[
E_{1j} = \frac{\sum_{d=1}^{D} \pi_d z_{dj}}{T} \leq 1, j = 1, ..., n
\]

\[
\sum_{d=1}^{D} \pi'_d z_{dj} \leq \sum_{i=1}^{m} v_i (1 - \omega_{ij}) x_{ij} + \sum_{p=1}^{P} \phi'_p H_{pj} + \sum_{b=1}^{B} \delta'_b F_{bj}
\]

\[
\sum_{d=1}^{D} \pi'_d z_{dj} \leq \sum_{i=1}^{m} v_i (1 - \omega_{ij}) x_{ij} + \sum_{p=1}^{P} \phi'_p H_{pj} + \sum_{b=1}^{B} \delta'_b F_{bj}
\]

\[
\sum_{d=1}^{D} \pi'_d z_{dj} \leq \sum_{i=1}^{m} v_i (1 - \omega_{ij}) x_{ij} + \sum_{p=1}^{P} \phi'_p H_{pj} + \sum_{b=1}^{B} \delta'_b F_{bj}
\]

Constraint (B.2):

\[
\sum_{i=1}^{m} v_i (1 - \omega_{i0}) x_{i0} + \sum_{p=1}^{P} \eta_p H_{p0} + \sum_{b=1}^{B} \delta_b F_{b0} = T
\]
\[
\sum_{i=1}^{m} v_i(1 - \omega_0) x_{i0} + \sum_{p=1}^{P} \eta_p H_{p0} + \sum_{b=1}^{B} \delta_b F_{b0} = 1
\]

\[
\sum_{i=1}^{m} v'_i x_{i0} - \sum_{i=1}^{m} \xi_{i0} x_{i0} + \sum_{p=1}^{P} \varphi'_p H_{p0} + \sum_{b=1}^{B} \delta'_b F_{b0} = 1
\]

Constraint (B.3):

\[L_i \leq \omega_{ij} \leq U_i, i = 1, 2, ..., m; \quad j = 1, 2, ..., n\]

\[L_i v'_i \leq \omega_{ij} v'_i \leq U_i v'_i, i = 1, 2, ..., m; \quad j = 1, 2, ..., n\]

\[L_i v'_i \leq \xi_{ij} \leq U_i v'_i, i = 1, 2, ..., m; \quad j = 1, 2, ..., n\]

\[
\max_{d=1}^{D} \sum_{d=1}^{D} \pi'_{d} z_{d0}
\]

s.t.

\[
\sum_{d=1}^{D} \pi'_{d} z_{dj} - \sum_{i=1}^{m} v'_i x_{ij} + \sum_{i=1}^{m} \xi_{ij} x_{ij} - \sum_{p=1}^{P} \varphi'_p H_{pj} - \sum_{b=1}^{B} \delta'_b F_{b0} \leq 0, j = 1, ..., n
\]

\[
\sum_{i=1}^{m} v'_i x_{i0} - \sum_{i=1}^{m} \xi_{i0} x_{i0} + \sum_{p=1}^{P} \varphi'_p H_{p0} + \sum_{b=1}^{B} \delta'_b F_{b0} = 1
\]

\[v'_i \geq 0, i = 1, 2, ..., m; \quad \pi'_d \geq 0, d = 1, 2, ..., D; \quad \varphi'_p \geq 0, p = 1, 2, ..., P;
\]

\[\delta'_b \geq 0, b = 1, 2, ..., B;
\]

\[L_i v'_i \leq \xi_{ij} \leq U_i v'_i, i = 1, 2, ..., m; \quad j = 1, 2, ..., n.
\]

REFERENCES

[1] A. Amirteimoori, A DEA two-stage decision processes with shared resources, Cent. Eur. J. Oper. Res., 21 (2013), 141–151.

[2] Q. An, F. Meng, B. Xiong, Z. Wang and X. Chen, Assessing the relative efficiency of Chinese high-tech industries: A dynamic network data envelopment analysis approach, Ann. Oper. Res., 290 (2020), 707–729.

[3] Q. An, Z. Wang, A. Emrouznejad, Q. Zhu and X. Chen, Efficiency evaluation of parallel interdependent processes systems: An application to Chinese 985 Project universities, Int. J. Prod. Res., 57 (2019), 5387–5399.

[4] Q. An, M. Yang, J. Chu, J. Wu and Q. Zhu, Efficiency evaluation of an interactive system by data envelopment analysis approach, Comput. Ind. Eng., 103 (2017), 17–25.

[5] A. Charnes, W. W. Cooper and E. Rhodes, Measuring the efficiency of decision making units, Eur. J. Oper. Res., 2 (1978) 429–444.

[6] C.-J. Chen, H.-L. Wu and B.-W. Lin, Evaluating the development of high-tech industries: Taiwan’s science park, Technol. Forecast. Soc. Change., 73 (2006), 452–465.

[7] K. Chen and J. Guan, Measuring the efficiency of China’s regional innovation systems: Application of network data envelopment analysis (DEA), Reg. Stud. 46 (2012), 355–377.

[8] K. Chen and M. Kou, Staged efficiency and its determinants of regional innovation systems: A two-step analytical procedure, Ann. Reg. Sci., 52 (2014), 627–657.

[9] X. Chen, Z. Liu and Q. Zhu, Performance evaluation of China’s high-tech innovation process: Analysis based on the innovation value chain, Technovation, 74-75 (2018), 42–53.

[10] Y. Chen, W. D. Cook, N. Li and J. Zhu, Additive efficiency decomposition in two-stage DEA, Eur. J. Oper. Res., 196 (2009), 1170–1176.

[11] Y. Chen, J. Du, H. D. Sherman and J. Zhu, DEA model with shared resources and efficiency decomposition, Eur. J. Oper. Res., 207 (2010), 339–349.
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[12] W. D. Cook and M. Hababou, Sales performance measurement in bank branches, *Omega*, 29 (2001), 229–307.

[13] W. D. Cook and L. M. Seiford, Towards a general non-parametric model of corporate performance, *Omega*, 192 (2009), 1–17.

[14] Q. Deng, S. Zhou and F. Peng, Measuring green innovation efficiency for China’s high-tech manufacturing industry: A network DEA approach, *Math. Probil. Eng.*, (2020).

[15] R. Färe and S. Grosskopf, Productivity and intermediate products: A frontier approach, *Econ. Lett.*, 50 (1996), 65–70.

[16] Z. Griliches, *Patent Statistics as Economic Indicators: A Survey*, University of Chicago Press, 1998.

[17] J. Guan and K. Chen, Measuring the innovation production process: A cross-region empirical study of China’s high-tech innovations, *Technovation*, 30 (2010), 348–358.

[18] J. Guan and K. Chen, Modeling the relative efficiency of national innovation systems, *Res. Pol.*, 41 (2012), 102–115.

[19] J. C. Guan, R. C. M. Yam, C. K. Mok and N. Ma, A study of the relationship between competitiveness and technological innovation capability based on DEA models, *Eur. J. Oper. Res.*, 170 (2006), 971–986.

[20] C. Guo and J. Zhu, Non-cooperative two-stage network DEA model: Linear vs. parametric linear, *Eur. J. Oper. Res.*, 258 (2017), 398–400.

[21] G. E. Halkos, N. G. Tzeremes and S. A. Kourtzidis, A unified classification of two-stage DEA models, *Surveys in Operations Research and Management Science*, 19 (2014), 1–16.

[22] C. Han, S. R. Thomas, M. Yang, P. Jeromonachou and H. Zhang, Evaluating R&D investment efficiency in China’s high-tech industry, *The Journal of High Technology Management Research*, 28 (2017), 93–109.

[23] H. J. G. M. Hollanders and F. Celikel-Esser, *Measuring Innovation Efficiency*, European Commission, 2007.

[24] Z. Hu, S. Yan, X. Li, L. Yao and Z. Luo, Evaluating the oil production and wastewater treatment efficiency by an extended two-stage network structure model with feedback variables, *J. Environ. Manage.*, 251 (2019), 109578.

[25] C. Kao, Network data envelopment analysis: A review, *Eur. J. Oper. Res.*, 239 (2014), 1–16.

[26] C. Kao and S.-N. Hwang, Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan, *Eur. J. Oper. Res.*, 185 (2008), 418–429.

[27] C. Kao and S. N. Hwang, Efficiency measurement for network systems: IT impact on firm performance, *Decis. Support Syst.*, 48 (2010), 437–446.

[28] J. Lee, C. Kim and G. Choi, Exploring data envelopment analysis for measuring collaborated innovation efficiency of small and medium-sized enterprises in Korea, *Eur. J. Oper. Res.*, 278 (2019), 533–545.

[29] C. Li, M. Li, L. Zhang, T. Li, H. Ouyang and S. Na, Has the high-tech industry along the belt and road in China achieved green growth with technological innovation efficiency and environmental sustainability?, *Int. J. Environ. Res. Public Health*, 16 (2019), 3117.

[30] H. Li, H. He, J. Shan and J. Cai, Innovation efficiency of semiconductor industry in China: A new framework based on generalized three-stage DEA analysis, *Socio-Econ. Plan. Sci.*, 66 (2019), 136–148.

[31] W. Li, Z. Li, L. Liang and W. D. Cook, Evaluation of ecological systems and the recycling of undesirable outputs: An efficiency study of regions in China, *Socio-Econ. Plan. Sci.*, 60 (2017), 77–86.

[32] Y. Li, Y. Chen, L. Liang and J. Xie, DEA models for extended two-stage network structures, *Omega*, 40 (2012), 611–618.

[33] L. Liang, W. D. Cook and J. Zhu, DEA models for two-stage processes: Game approach and efficiency decomposition, *Nav. Res. Log.*, 55 (2008), 643–653.

[34] L. Liang, F. Feng, W. D. Cook and J. Zhu, DEA models for supply chain efficiency evaluation, *Ann. Oper. Res.*, 145 (2006), 35–49.

[35] L. Liang, Z.-Q. Li, W. D. Cook and J. Zhu, Data envelopment analysis efficiency in two-stage networks with feedback, *IEEE. Trans.*, 43 (2011), 309–322.

[36] S. Lin, R. Lin, J. Sun, F. Wang and W. Wu, Dynamically evaluating technological innovation efficiency of high-tech industry in China: Provincial, regional and industrial perspective, *Socio-Econ. Plan. Sci.*, (2021), 100939.
[37] Z. Liu, X. Chen, J. Chu and Q. Zhu, Industrial development environment and innovation efficiency of high-tech industry: Analysis based on the framework of innovation systems, Technol. Anal. Strateg. Manage., 30 (2018), 434–446.

[38] W. Nasierowski and F. J. Arcelus, On the efficiency of national innovation systems, Socio-Econ. Plan. Sci., 37 (2003), 215–234.

[39] L. M. Seiford and J. Zhu, Profitability and marketability of the top 55 US commercial banks, Manage. Sci., 45 (1999), 1270-1288.

[40] Q. Shen, Measuring the R&D Performance of High-Tech Manufacturing Sectors in China: A Data Envelopment Analysis Application, J. Comput. Theor. Nanosci., 13 (2016), 7773–7778.

[41] X. Shi, Environmental efficiency analysis based on relational two-stage DEA model, RAIRO-Oper. Res., 50 (2016), 965–977.

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

[43] F.-M. Tseng, Y.-J. Chiu and J.-S. Chen, Measuring business performance in the high-tech manufacturing industry: A case study of Taiwan’s large-sized TFT-LCD panel companies, Omega, 37 (2009), 686–697.

[44] C. H. Wang, R. D. Gopal and S. Zionts, Use of data envelopment analysis in assessing information technology impact on firm performance, Ann. Oper. Res., 73 (1997), 191–213.

[45] Q. Wang, Y. Hang, L. Sun and Z. Zhao, Two-stage innovation efficiency of new energy enterprises in China: A non-radial DEA approach, Technol. Forecast. Soc. Change., 112 (2016), 254–261.

[46] Y. Wang, J.-F. Pan, R.-M. Pei, B.-W. Yi and G.-L. Yang, Assessing the technological innovation efficiency of China’s high-tech industries with a two-stage network DEA approach, Socio-Econ. Plan. Sci., 71 (2020), 100810.

[47] H. Wu, K. Lv, L. Liang and H. Hu, Measuring performance of sustainable manufacturing with recyclable wastes: A case from China’s iron and steel industry, Omega, 66 (2017), 38–47.

[48] J. Wu, Q. Zhu, J. Chu, H. Liu and L. Liang, Measuring energy and environmental efficiency of transportation systems in China based on a parallel DEA approach, Transp. Res. D. Transp. Environ., 48 (2016), 460–472.

[49] J. Wu, Q. Zhu, X. Ji, J. Chu and L. Liang, Two-stage network processes with shared resources and resources recovered from undesirable outputs, Eur. J. Oper. Res., 251 (2016), 182–197.

[50] A. Yu, Y. Shi, J. You and J. Zhu, Innovation performance evaluation for high-tech companies using a dynamic network data envelopment analysis approach, Eur. J. Oper. Res., 292 (2021), 199–212.

[51] Y. Zha and L. Liang, Two-stage cooperation model with input freely distributed among the stages, Eur. J. Oper. Res., 205 (2010), 332–338.

[52] B. Zhang, Y. Luo and Y.-H. Chiu, Efficiency evaluation of China’s high-tech industry with a multi-activity network data envelopment analysis approach, Socio-Econ. Plan. Sci., 66 (2019), 2–9.

[53] C. Zhang and Y. Lin, Panel estimation for urbanization, energy consumption and CO2 emissions: A regional analysis in China, Energy Policy, 49 (2012), 488–498.

[54] L. Zhao, Y. Zha, Y. Zhuang and L. Liang, Data envelopment analysis for sustainability evaluation in China: Tackling the economic, environmental, and social dimensions, Eur. J. Oper. Res., 275 (2019), 1083–1095.

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E-mail address: wdu1996@mail.ustc.edu.cn
E-mail address: lin87@mail.ustc.edu.cn
E-mail address: fengyang@ustc.edu.cn
E-mail address: ckh0605@mail.ustc.edu.cn