Distribution and Evolution of Industrial Innovation Efficiency

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Abstract—We propose a two-stage model of Data Envelopment Analysis (DEA) to assess the innovation efficiency of the innovative effort for Chinese industries. The first stage is to measure the technology efficiency and the second is to measure the economy efficiency. The integral stage is the combination of the two stages and to evaluate integral efficiency for the whole innovative process. For different evaluating purposes, two kinds of DEA models, namely CCR and BCC, are used to measure the innovation efficiency and analyze evolution of innovation efficiency of Chinese Industries during the recent years, respectively. The results indicate that most of Chinese industries have a relative high efficiency in the first stage, however, and a low efficiency in the second stage. Mediocre efficiency occurs for most of Chinese industries in the integral stage. This reveals there are some serious inconsistencies between technology capability and economic performance in most Chinese industries and their capability of transforming technology efficiency to economy is relatively poor. Research results further show that there is still much room for Chinese industries to improve their innovation efficiency. The findings reveal that the heavy investment in R&D alone can neither bring high S&T output, nor competitive advantages.

I. INTRODUCTION

The economic performance and competitiveness of the industries will be substantially determined by their innovation efficiency. It is now widely accepted that the technological innovation is crucial to the growth of economic output, productivity and employment of nations. In consideration of the great effects of science and technology (S&T) on the economic status and the unavoidable limitation of natural resources, technological innovation is also widely admitted to be indispensable for industrial sustainable and harmonious development. Many studies found that technological innovation could make positive impacts on enhancing the competitiveness of firms [12], [13], [22], [23], [33].

Evaluating industrial innovation efficiency is vital for an industry in its formulation of its R&D strategy, design process flow and marketing strategy [25], [26], [27]. Earlier studies in this regard were either confined to the traditional strategy analysis framework or mainly focused on financial indicators. In general, they merely provided lists of innovation factors and did not explain the formation of internal mechanism of innovation. The interaction relationship between S&T and economy during innovation process, however, has not been enough emphasized. One of the major problems in evaluating the efficiency of industrial innovation is the lack of a good estimate of the production function to link the interaction relationship between S&T and economy during innovation process.

To solve the lack of a good estimate of the production function, the relative efficiency of the concerned “units” should be introduced. The breakthrough in this regard came in the research work carried out by Charnes et al. [6]. This was the first paper using the technique of Data envelopment analysis (DEA). Data envelopment analysis (DEA) uses a mathematical programming model to estimate best-practice frontiers without a priori underlying functional form assumption through computing multi-input/multi-output values. Since the first CCR DEA model was put forward by Charnes et al. [6], a number of different DEA models and their corresponding real-world applications have appeared in literature [11], [32], [36]. Joro et al. [17] studied the relationship between DEA and multiple criteria decision making (MCDM). The MCDM tools can be used to perform the projections to the efficient frontier. DEA can be used to optimize the performance measure of each decision making unit (DMU). DEA calculates a maximal performance measure for each DMU relative to all DMUs under observation. In other words, the focus of DEA is on the individual observations as represented by n optimizations (where n is the number of DMUs), in contrast to the focus on the averages and estimation of parameters that are associated with a single optimization statistical parametric approach. The major advantage of the DEA approach is that DEA does not require any assumptions about the function form. That means that DEA does not need any priori information on the underlying functional forms and weights among various input and output factors. The performance measure of a multiple inputs and multiple outputs production system can hardly be described by a concrete function form. Therefore, DEA is particularly suitable for analyzing multiple inputs and multiple outputs production systems [7], [35], [36].

DEA has been widely used in different industrial sectors in the area of industrial management for performance evaluation and benchmarking studies [35], [36]. For example, Zhu [35] employed DEA to explore the multi-dimensional financial performance of Fortune 500 companies. Thus there is a high potential for DEA applications to examine the multi-factor competitiveness performance of a company or an industry if a similar analysis framework is adopted. In this case, innovation capability indicators and competitiveness indicators will be taken respectively as inputs and outputs of the DEA model. For example, Guan et al. [16] adopted data envelopment analysis to explore the quantitative relationship between technological innovation capability and competitiveness at enterprise level.

DEA has also been extensively used in the areas of
science and technology (S&T) management and information management for performance evaluation and benchmarking studies. For example, Rousseau and Rousseau [30], [31] used data envelopment analysis to measure research efficiency of European nations. Guan and Wang [14] employed data envelopment analysis to measure relative knowledge production efficiency of research groups in the field of information science and technology.

In the present study, data envelopment analysis is adopted to explore industrial innovation efficiency at industrial level for Chinese industry. The VRS model of DEA techniques will be used to measure technology efficiency and its evolution during innovative process. On the other hand, The CCR of DEA techniques will be used to analyze simultaneously technology efficiency and scale efficiency at individual phases during innovative process for Chinese industry.

The remaining parts of the paper are organized as follows. Section 2 introduces a two-stage conceptual framework to analyze transformation procedure from inputs to outputs of innovation process. Section 3 describes methods used by the study and explains how DEA technology is applied to the proposed two-stage framework. Section 4 provides the important empirical findings of evaluating Chinese industries' technological and economic efficiency. The integrative efficiency for the total innovative process and evolution of industrial innovation efficiency are also reported in the section. A concluding section provides the policy suggestions, which aim at resolve the revealed inequalities amongst the Chinese industrial innovation systems.

II. CONCEPTUAL FRAMEWORK AND INDICATORS

The innovation process is essentially a knowledge and wealth generation process, in which one utilizes resources (R&D personnel, R&D investment, expenditure of technology import, and so on) to create new knowledge and increase economic wealth. Acx et al. [2] use patents counts as a proxy measure of innovative activity. Following up the methodology, Guan and Liu [15] use the number of national invention patent applications examined as an indicator to measure the innovative capacity for China’s 30 provinces, because patents offer a number of advantages as the indicator of the outcome of R&D activity. However, each single performance measure may be unsatisfactory in characterizing overall innovative performance of industry. This is because the complex interactions between S&T and economy during innovation processes related to industry and the specific industrial characters in S&T and innovative activities have been insufficiently understood.

Industrial innovation systems' performance is a complex phenomenon and an outcome of interactions between S&T and economy, which requires multi-criteria to characterize it. The development of a multi-factor performance measurement, which reconciles diverse measures, is important to policy makers by knowing how far a particular industrial innovation system can be expected to increase its multiple outputs and decrease its inputs. Data envelopment analysis (DEA), which will be in detail reported in the next section, is particularly suitable for analyzing multiple inputs and multiple outputs production systems [35]. The overall hypothesis in this work advocates that the innovation efficiency of industry is jointly and interactively affected by multiple input and output factors, rather than a single index. To focus on measuring the innovation efficiency of Chinese industry and consider the availability of the data, we analyze and evaluate Chinese industrial innovation efficiency mainly by ten input and output indicators to characterize Chinese industrial innovation performance.

In this paper, we adopt DEA technology as an alternative approach to reconcile major measures via a two-stage transformation process described in Fig. 1. The two-stage transformation process is defined in terms of the ten indicators, which is popularly recognized and used in the evaluation of Chinese industrial innovation system's efficiency. In doing so, the interaction relationship between S&T and economy during innovation process is highly emphasized. Accordingly, multiple indicators approach is employed in terms of the proposed framework in order to enhance reliability and validity of the efficiency measurement.
A. Inputs and outputs of the stage-1

In the first stage of Fig. 1, we concentrate on the technology efficiency of the upstream activities in innovative process at industrial level, namely transformation efficiency from S&T inputs to S&T outputs. This stage deals with the efficiency issue of S&T inputs and outputs for industrial innovation system. The input factors in the first stage can be divided into two aspects: S&T human resource and S&T financial resource. S&T human resource is measured by ratio of S&T personnel to total employee of the concerned industry, indicated by $X_{11}$. The previous empirical evidences [16] showed that the adoption of transferred and/or purchased technologies has strong impacts on technological innovation performance of Chinese firms and many Chinese firms have been relying largely on costly generation technologies (e.g., key equipment and apparatuses) and improvement of key technology equipment. Therefore, in present study S&T financial resource consists mainly of four financial indicators, including:

- $X_{12}$: ratio of in-house R&D expenditure to total in-house expenditure,
- $X_{13}$: technology import expenditure abroad,
- $X_{14}$: technology acquisition expenditure from mainland and
- $X_{15}$: expenditure to improve technology equipment.

It may be more rational if R&D funds and the number of R&D personnel were used as inputs in the first stage. However, the paucity of available statistical data for the considered time span has restricted this approach. For example, the data of R&D expenditures are not available at industrial level for the studied period from all Chinese statistic yearbooks. Instead, the indicators above mentioned are accessible and are often used to evaluate innovation efficiency at industrial level in the context of China [5], [10], [28].

The outputs of the first stage are intermediate products of innovative process. Patents are important indicators of innovation [3], [15], [18], [19]. In this study, we use patents applications of industry, $Y_{11}$, to indicate the innovative capability of the industry. On the other hand, product innovation is better measurable than process innovation [24]. This is particularly true when we prepare the data for the present study in terms of Chinese statistics. Therefore, the number of new product development projects, $Y_{12}$, is adopted to describe one of technology outputs of R&D investment. In Guan and Liu's work, they considered two years delay from R&D investment to patent application in Chinese context [15]. In this study, following their method, we take two years' delay between inputs and outputs in each phase of the innovation process. The performance in the first stage (stage-1) should be viewed as technology efficiency.

B. Inputs and outputs of the stage-2

The first stage only deals with the transformation efficiency of Chinese industry from technological investment to technological output. The ultimate goal of technological innovation is, however, to transform S&T achievement to economy efficiency and accelerate sustainable economic growth. According to Moon and Lee [21] and OSILO manual [24], patent variable and new product development projects are not only R&D outputs, but also play important roles in economic activities of firms as well as industry. However, patents and new product development projects cannot describe the performance of economic activities of an industry although they can measure new technology very well [1], [2]. Therefore, patents and new product development projects, which characterize outputs of the first stage, are of course regarded as inputs of the second stage, as described in Fig. 1. The performance in the second stage (Stage-2) may be viewed as economic efficiency. That is, in the second stage, the economic efficiency of the downstream activities of innovative process is emphasized. Thus, the economic indicators that are available in “China Statistical Yearbooks” are employed as the economic outputs of the second stage. The economic indicators include Share of New Products Sales over Total Sales, Overall Labor Productivity and Value-added.

Finally, the inputs in the first stage, as well as the outputs in the second stage, are used to characterize the whole performance of innovative activities in the integration stage (stage-3). By using the two-stage conceptual framework, the efficiencies of industrial innovation systems can be examined more intensive and insightful.

C. Data

All the data at industrial level used in this paper are derived from China Statistical Yearbook and China Statistical Yearbook on Science and Technology from 1996 to 2005 published by National Bureau of Statistics & Ministry of Science and Technology. 35 industries, with a timespan of ten years ranged from 1996 to 2005, are used as Decision Making Units (DMUs) in the DEA analysis. Moreover, all the economic data are deflated by the Chinese Retail Price Index by taking 1997 as the base year.

III. METHODS

DEA was developed from the perspective of “relative efficiency evaluation” by Charnes et al. [6]. It is a systematic technique to measure relative efficiency amongst DMUs (Decision Making Units), and it is often applied in evaluations of multi-inputs and multi-outputs, e.g., the multi-product industry measurement [29] and firms' innovation capabilities and competitiveness measurement [16]. The first evaluation of macroeconomic activities of Chinese cities based on DEA was carried out by Charnes et al. [8]. The efficiency of resource allocation can also be assessed by DEA models [34]. In the past few years, DEA becomes more and more popular in assessing practice or
In this paper, we use CCR and CCGSS (i.e., BCC) model in DEA [35] to assess the relative technology efficiency as well as economy efficiency of Chinese industry.

First, the traditional input-oriented constant returns scale (CRS) DEA model [6] was used in this paper to determine the best-practice frontier. The technical efficiency problem for a \( DMU_0 \) (here means the \( j_0 \)th industry) can be expressed by the following CCR model:

\[
\begin{align*}
\min & \quad \theta_o \cdot \varepsilon (\sum_{j=1}^m \lambda_j x_{j0} + \sum_{j=1}^m \delta_j^+), \\
\text{s.t.} & \quad \sum_{j=1}^m \lambda_j x_{j0} + \sum_{j=1}^m \delta_j^+ = \theta_o x_{i0}, \quad i = 1, 2, \ldots, m, \\
& \quad \sum_{j=1}^m \lambda_j y_{j0} - \sum_{j=1}^m \sigma_j^* y_{i0} = y_{i0}, \quad r = 1, 2, \ldots, s, \\
& \quad \theta_o, \lambda_j, \delta_j^+, \sigma_j^* \geq 0
\end{align*}
\]

where \( n \) is the number of DMUs, \( m \) and \( s \) indicate the number of inputs and outputs respectively. In the first stage that examines the technology efficiency, \( m = 5 \) and \( s = 2 \). In the second stage (economy efficiency examination), \( m = 2 \) and \( s = 3 \). Thus, in the integrative stage (the integration of stage-1 and stage-2), \( m = 5 \) inputs in stage-1 and \( s = 3 \) outputs in stage-2. \( \theta_o \) in the formula (1) is the objective function’s value; \( 0 < \varepsilon < 1 \) is a non-Archimedean infinitesimal, which is employed to overcome the difficulties of testing multi-optimum solutions; \( \delta_j^+ \) is convex coefficient, \( x_{i0} \) is the \( i \)th input for industrial innovation system \( j_0 \), \( i = 1, 2, \ldots, m \); \( y_{r0} \) is the \( r \)th output for industrial innovation system \( j_0 \), \( r = 1, 2, \ldots, s \); \( \delta_j^+ \) and \( \sigma_j^* \) are input and output slack variables respectively. Each DMU \((j=1, 2, \ldots, n)\) produces \( s \) different outputs \( y_{r0} \) (\( r = 1, 2, \ldots, s \)) utilizing different inputs \( x_{i0} \) (\( i = 1, 2, \ldots, m \)).

If, in optimality, \( \theta_o^*=1 \) and all input and output slack variables, \( \delta_j^+ \) and \( \sigma_j^* \), are equal to zero, then industrial innovation system \( j_0 \) is CRS-efficient and is operating on the CRS frontier. Otherwise, if \( \theta_o^* \neq 1 \), and/or some input/output slacks are nonzero, then industrial innovation system \( j_0 \) is CRS-inefficient, which implies that some latent and industrial innovation system-specific resources are still not being penetrated and not being fully utilised. This indicates its efficiency cannot be tapped effectively. The inefficiency could be caused by inefficient harmonizing and integrating of various input resources within the industrial innovation system. The value of \( \theta_o^* \) measures the input savings by a possible proportional input reductions. In practice, \( \theta_o^* \) can be considered to be a possible reduction proportion (gap) of input resources from the optimality frontier. The smaller the \( \theta_o^* \) is, the worse the efficiency of the industrial innovation system. By varying the specific index over all industrial innovation system, we have the CRS best practice frontier.

According to the CCR model (1), DMUs that are operating in best-practice frontier represent both “technical” efficiency and “scale” efficiency [35]. However, in practice, increasing or decreasing returns to scale (IRS or DRS) for those CRS-inefficient industrial innovation system is likely to happen. It is thus necessary to analyze the “scale” efficiency of all the studied industrial innovation system. By incorporating an additional constraint of \( \sum_{j=1}^m \delta_j = 1 \) into the CCR model (1), the so called “BCC” model is obtained as shown in the following expressions [35]:

\[
\begin{align*}
\min & \quad \sigma_o - \varepsilon (\sum_{j=1}^m \delta_j^+ + \sum_{j=1}^m \sigma_j^*), \\
\text{s.t.} & \quad \sum_{j=1}^m \lambda_j x_{j0} + \sum_{j=1}^m \delta_j^+ = \sigma_o x_{i0}, \quad i = 1, 2, \ldots, m, \\
& \quad \sum_{j=1}^m \lambda_j y_{j0} - \sum_{j=1}^m \sigma_j^* y_{i0} = y_{i0}, \quad r = 1, 2, \ldots, s, \\
& \quad \sigma_o, \lambda_j, \delta_j^+, \sigma_j^* \geq 0
\end{align*}
\]

where \( \sigma_o^* \) is an efficiency score of variable returns to scale (VRS) provided by BCC model. Similarly, if \( \sigma_o^* = 1 \), \( DMU_0 \) is VRS-efficient, otherwise, \( \sigma_o^* < 1 \), \( DMU_0 \) is VRS inefficient.

Model (2) can be used to determine the “technical” efficiency, but not the scale efficiency [35]. We can define the returns to scale (RTS) by the ratio of a CRS score of model (CCR) to a VRS score of model (BCC), i.e., \( \theta_o^* / \sigma_o^* \). If the ratio is equal to one, i.e., \( \theta_o^* / \sigma_o^* = 1 \), then industrial innovation system \( j_0 \) is “scale” efficient; otherwise if the ratio is less than one, i.e., \( \theta_o^* / \sigma_o^* < 1 \), the industrial innovation system \( j_0 \) is “scale” inefficient. Therefore, we need to determine whether IRS or DRS is the primary cause of “scale” inefficiency. Zhu and Shen [37] provide a good method to solve this problem. That is, if the CRS score is equal to the VRS score, i.e., \( \theta_o^* = \sigma_o^* \), then CRS prevails; otherwise, if the CRS and VRS score are not equal, i.e., \( \theta_o^* \neq \sigma_o^* \), then \( \sum_{j=1}^m \delta_j^+ < 1 \) in CCR model indicates IRS while \( \sum_{j=1}^m \delta_j^+ > 1 \) indicates DRS.
IV. RESULTS

In order to better explore distribution and evolution of industrial innovation efficiency, we first need to classify the industrials according to their innovative capacity. We still use the sum of national patent applications examined as proxy indicator of innovative capacity for the different industries over ten years (from 1996 to 2005) to measure the industrial innovative capacity [2], [15]. The authors carefully collected these original databased on China’s statistical yearbooks from the various years and further summed them up.

Initial cluster centres and the number of clusters can be specified from information on the industrial innovative capacity, so we choose K-Means Cluster Analysis according to characteristics of this algorithm [20]. This means we classify and cluster the concerned industries according to Euclid distances. With K-Means cluster analysis, we could cluster China’s 35 industries into three homogeneous groups based on the innovative capacity. The cluster results are described in Table 1, ranked from the industries with high innovative capacity to those with a low one. The values in the parenthesis of column 1 in Table 1 represent group centers for the different groups. The values in the parenthesis of column 2 in Table 1 indicate the Euclid distances from the group centre.

<table>
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<tr>
<th>TABLE 1</th>
<th>THE K-MEANS CLUSTER OF INNOVATION CAPACITY</th>
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<tbody>
<tr>
<td>Industries with high innovation capacity (7266)</td>
<td>Electric Equipment and Machinery(21167), Electronic and Communication(16564), Transport Equipment(6616), Raw Chemical Material and Chemical Products(1136), Pharmaceutical(960), General Machinery(674), Special Machinery(1423)</td>
</tr>
<tr>
<td>Industries with middle innovation capacity (3822)</td>
<td>Textile(683), Metal Products(649), Instruments and Meters(329), Culture, Educational and Sports Goods(29), Nonmetal Metal Products(1 26), Petroleum and Natural Gas(260), Beverage(295), Food Production(316), Smelting and Pressing of Ferrous Metal(693)</td>
</tr>
<tr>
<td>Industries with low innovation capacity (864)</td>
<td>Production and Supply of Gas(808), Nonferrous Metals Mining and Dressing(778), Timbers(670), Nonmetal Minerals Mining and Dressing (661), Leather(564), Printing and Record Medium Reproduction(447), Tobacco(436), Chemical Fiber(387), Papermaking(345), Furniture(209), Production and Distribution of Water(182), Textile Wearing Apparel(81), Rubber Products(36), Processing of Food(55), Production and Supply of Electric and Heat Power (230), Mining and Washing of Coal(376), Processing of Petroleum(1060), Plastic Products(1165), Smelting and Pressing of Nonferrous Metal (1472) Other Manufacturing(1168)</td>
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</table>

A. CRS efficiency

In this study, the programs based on Matlab 6.5 software are used to compute the optimal values for the DEA approaches. Therefore, we are able to determine the relative CRS efficiency via the CCR model (1) and VRS efficiency by BCC model (2). After the deflation for the economic data, we put all 175 DMUs in each stage (35 industries in five time spans) in one model. According to Charnes, et al. [8], the efficiency scores in different years of an industry can describe the efficiency trend of the industry when we put the data of all industries in different years in one model.

We examine CRS efficiency and Return to Scale (RTS) for each DMU by varying the index ‘α’ in the formula (1) in each stage. With K-Means cluster analysis, we could also cluster China’s 35 industries into three homogeneous groups based on the innovative efficiency. The cluster results are described in Table 2.

The CRS efficiency for the industries with high innovation capacity is indicated in Table 3. The values in the parenthesis are CRS ones.
Table 2 indicates that most of industries with high innovation capacity have achieved high technology efficiency at stage-1, except for Raw Chemical Material and Chemical Products. In terms of CRS, five industries at stage-1, namely Electric Equipment and Machinery, Electronic and Communication, Transport Equipment, General Machinery and Special Machinery, are operating on the best-practice frontier. In addition, they achieve constant return to scale. Pharmaceutical is operating in high efficiency but in DRS at stage-1. This indicates the industry should pay more attentions to enhance its technology transformation efficiency. The industry, Raw Chemical Material and Chemical Products, obtains a lowest CRS value at stage-1 and operates in IRS. This shows that the industry should increase its technology inputs.

Strikingly, all industries with high innovative capacity are CRS inefficient at stage-2. Furthermore, research results in Table 3 indicate that these CRS inefficient industries are operating on the DRS frontier at stage-2. The results reveal that although the group of industries tries to improve their technological innovation capability continually, their economic competitiveness is still unsatisfactory. These industries should make greater efforts to reform their internal innovation harmonizing process to improve economic efficiency of innovation. The findings reveal that the heavy investment in R&D alone can neither bring high S&T output, nor competitive advantages.

Table 4 indicates that only three industries with middle innovation capacity, namely, Textile, Instruments and Meters, Culture, Educational and Sports Goods, have achieved high innovation efficiency at stage-1. Among them, two industries, Instruments and Meters, Culture, Educational and Sports Goods, achieve constant return to scale. The two industries are operating on the best-practice frontier and they are both technology and scale efficiency at stage-1. Other six industries are technology inefficient and are operating in IRS at stage-1. This shows that the six industries should significantly increase their technology inputs.

Again, strikingly, almost all industries with middle innovative capacity are CRS inefficient at stage-2, except for Petroleum and Natural Gas. Furthermore, calculation results indicate that the eight industries CRS values are all less than or equal to 0.22. The finding again reveals that the investment in R&D alone can not bring competitive advantages. These eight industries should make greater efforts to reform their internal innovation harmonizing process to improve economic efficiency of innovation.

Table 5 indicates that only one industry with low innovation capacity, furniture, is operating on the best-practice frontier and it is both technology and scale efficiency at stage-1. Other all industries with low innovation capacity are technology inefficient and are operating in IRS at stage-1. This shows that almost all industries with low innovation capacity can enhance their technology efficiency through significantly increasing their technology inputs.

Four industries, i.e., Tobacco Timbers Production and Distribution of Water Production and Supply of Gas within the group with low innovation capacity, are operating on the best-practice frontier and they are both technology and scale efficiency at stage-2, namely economy transformation phase. However, these four industries are technology inefficient and in IRS at stage-1. This indicates that enhancement of technology efficiency is a key to improve their economy efficiency for these industries. Other industries should make greater efforts to reform their internal innovation harmonizing process to improve economic efficiency of innovation.
The results indicate that most of Chinese industries have a relative high efficiency in the first stage, however, and a low efficiency in the second stage. This reveals that there are some serious inconsistencies between technology capability and economic performance in most Chinese industries and their capability of transforming technology efficiency to economy is relatively poor. The findings in general uncover that there is still much room for Chinese industrial innovation systems to improve their efficiency in situations of confining industrial innovation systems' resources inputs.

**B. VRS efficiency**

We now determine the relative VRS efficiency via BCC model (2) and observe its dynamic evolution. Fig. 2 summarizes the distributions of the average VRS efficiency scores for the studied 35 industries across all stages during the studied period. Average VRS scores of 57.1% industries are distributed between 0.55 and 0.95 at stage-1. Only for one industry, its average VRS efficiency score at stage-1 is less than 0.3. For 40% of the industries, their average VRS efficiency scores at stage-1 are more than 0.8. This indicates that Chinese industry achieves relative higher efficiency in transformation from research & development to technological outcomes during their industrial innovation activities as a whole, although there is a significant difference between different industries.

As described in Fig. 1, the first stage is to measure the technology efficiency and the second is to measure the economy efficiency. Fig. 2 and Fig. 3 indicate that there is significant difference in average efficiency scores between stage-1 and stage-2. Through evaluating the relative efficiency of two stages (technology and economy) of China’s industries, we find that the efficiency in stage-1 is much better than that in stage-2. There are twenty three industries, namely 65.7% of the studied industries, whose average VRS efficiency scores at stage-2 are below 0.3, sharply contrasted to ones at stage-1. Only for two industries, i.e., 5.7% of the studied industries, their average VRS efficiency scores at stage-2 are more than 0.8. As a whole, Chinese industries are inefficient in transformation from technological outcomes to economy during their industrial innovation activities. This shows that the most of Chinese industries have a relative high efficiency in the first stage, however, and a low efficiency in the second stage. Fig. 2 also indicates that mediocre efficiency occurs for most of Chinese industries in the integral stage.

![Table 5: CRS and RTS for MIDDLE GROUP](image)

![Fig. 2: Average efficiency distributions for all stages](image)

![Fig. 3: Percentage distributions of average efficiency for all stages](image)

**C. Evolution**

In order to understand the evolvement process of industrial innovation efficiency for Chinese industrial
innovation systems, we need to draw dynamic curves of industrial innovation efficiency for all studied industries and all stages across all studied time span. Typically, we report here the evolution process of industrial innovation efficiency for the group with high innovation capacity across the time span 2000-2004. Fig. 4, Fig. 5 and Fig. 6 present dynamic curves of industrial innovation efficiencies for stage-1, stage-2 and integral stage, respectively.

![Fig. 4 Evolution of industrial innovation efficiency at stage-1](image1)

![Fig. 5 Evolution of industrial innovation efficiency at stage-2](image2)

![Fig. 6 Evolution of industrial innovation efficiency at integral stage](image3)

Fig. 4 indicates that from the viewpoint of dynamic evolution, most of the studied industries, except for Chemicals, achieve relative higher efficiency from technology input to technology output, although they fluctuate understandably a little bit during the studied period. In contrast, the performance of transformation from research & development to technological outcomes of the Chemicals is relative low, fluctuating about at 0.45. The industry should pay more attention to enhancement of technology efficiency than other industries do.

On the other hand, as shown in Fig. 5, the efficiency of transforming technological outcomes to economical performance for most of the studied industries and most years is extremely low, except for electronic at 2003 and 2004 and transport at 2003. The average VRS scores for most DMUs are between 0 and 0.1. This sharply contrasts to the results at stage-1. It can be seen from Fig.s 4 and 5 that for almost all industries with a high innovation capacity in China, the average innovation efficiency scores at the corresponding year of stage-1 are much higher than ones at the same year of stage-2. The evolution results further support the previous findings in previous subsections CRS efficiency and VRS efficiency.

Fig. 6 again shows that mediocre efficiency occurs for most of Chinese industries in the integral stage from viewpoint of dynamic evolution. This is understandable and not strange when we take into account that the integral stage is combined by the inputs of stage-1 and outputs of stage-2. However, it seems impossible to give a monomodal explanation for the observed differences between the individual industries. Anyway, our findings reveal that the investment in R&D alone can neither bring high S&T output, nor competitive advantages in economy.

![Fig. 7 Evolution of industrial innovation efficiency at integral stage](image4)

Again, we can conclude that from evolution viewpoint, the performance of transformation from research & development to technological outcomes is much better than that of transforming technological outcomes to economical performance in China's industry. The lower efficiency of transforming technological outcomes to economical performance in China's industry impedes the enhancement of innovation efficiency of Chinese industry as a whole. This result indicates that most industries have a big potential in improving their economic efficiency than technological efficiency. Therefore, an increase of the efficiency on transforming technological outcomes to economical performance is the more effective way to improve the industrial innovation efficiency than increasing technology input for Chinese industries.

**V. CONCLUSIONS**

By using DEA, this paper explores the multidimensional technological and economical performance of 35 industries in China in recent years. We evaluate the CRS and VRS efficiencies of Chinese industrial innovation systems via the CCR and BCC models. The scale efficiency and evolution of innovation efficiency of Chinese industries are also further taken into account.
Evidences show that most industries with high innovation capacity are of high technology efficiency at stage-1. Strikingly, in terms of CRS, no industry with high innovation capacity in the stage-2 is operating on the best-practice frontier. This reveals that there are some serious inconsistencies between technology capability and economic performance in most Chinese industries. Their capability of transforming technology efficiency to economy is relatively poor. The findings also show that heavy investment in S&T, although necessary for catching up countries, does not necessarily bring high efficiency for Chinese industries during their innovation activities and can not guarantee success in innovation, either. The findings in general uncover that there is still much room for Chinese industries to improve their efficiency in situations of confining industrial innovation systems’ resources inputs.

Our findings are of great important policy implications. Chinese industries should change their emphasis from current sharply increasing S&T investment to harmonizing tradeoffs between multidimensional innovative resources. Only in this way, the investment could be returned in an efficient manner. In order to sustain a high growth rate through technological innovation and reduce industrial inequality with respect to S&T capability and economic competitiveness, Chinese government needs to formulate specific S&T policies to support technological developments of those less developed industries. More importantly, Chinese government may need to restructure the science sector, in terms of giving higher priority to those relative weak industries’ specific R&D and innovation efforts.

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