Network DEA approach for measuring the efficiency of University-Industry Collaboration Innovation: Evidence from China

Yu Yu[1] , Qinfen Shi[2] and Jie Wu [3]

[1] *yuyu0801@139.com*
Hohai University, Business School, No.8 Focheng Road West, 211100 Nanjing (China)

[2] *shiqf@njupt.edu.cn*
Nanjing University of Posts and Telecommunications, School of Management, No.9 Wenyuan Road, 210023 Nanjing (China)

[3] *0511wujie@163.com*
Jiangsu University of Science and Technology, School of Economics and Management, No.2 Mengxi Road, 212003 Zhenjiang (China)

Introduction

Collaborative innovation is a trans-disciplinary approach for developing the wholeness synergy to improve the competitiveness of an organization through holistic, competitive and complementary interactions between and among innovation participants in a specific environment (Bommert, 2010; Swink, 2006). The collaborative innovation system essentially consists of three sectors: industry, universities, and the government, with each sector interacting with the others, while at the same time playing its own role. Collaborative innovation system is a complex conglomerate of interacting independent parties. The network of institutional relations among universities, industries, and governmental agencies has been considered as a Triple Helix (TH). Collaborative innovation system (CIS) is based on a multi-input, multi-output transformation relation. It is an important issue to investigate the performance related to the transformation process of limited innovation resources for improving collaborative innovative outputs. Previous studies have been done to evaluate the performance of collaborative innovation. However, those studies failed to consider the complexity of the collaborative innovation system. Data envelopment analysis (DEA) is a method for measuring the efficiency of peer decision making units (DMUs). Recently network DEA models been developed to examine the efficiency of DMUs with internal structures. The internal network structures range from a simple two-stage process to a complex system where multiple divisions are linked together with intermediate measures. In this study, we propose a network DEA with parallel production systems to measure the efficiency of University-Industry Collaborative Innovation. The purpose of the present study is to construct a complete measurement framework characterizing the CIS' production framework from original S&T investment to final outputs, and measure the CIS' process-oriented technical efficiency, which is implemented in China's context. It is hoped that this study will benefit China's collaborative innovation policy-making.

Network DEA model

We propose a network DEA with parallel production systems in this section. Assume that there are n DMUs, and each DMU has two *sub-DMUs*. Figure 1 depicts the visual structure of the DEA model.

The part of inputs is consumed by SDMU1 and SDMU2 together, and part of DMU output is co-produced by SDMU1 and SDMU2. Besides, some inputs and outputs are consumed or produced by SDMU1 or SDMU2 alone. Variables are defined as follows: $X_1 = (x_{1j}^1, \ldots, x_{mj}^1)$ represent *m* separate inputs which are consumed by SDMU1; $X_2 = (x_{1j}^2, \ldots, x_{hj}^2)$ represent *h* separate inputs which are consumed by SDMU2; $X_s = (x_{1j}^s, \ldots, x_{lj}^s)$ represent *l* inputs consumed by SDMU1 and SDMU2 together. The vector of $Y_1 = (y_{1j}^1, \ldots, y_{sj}^1)$ are *s* outputs produced by SDMU1; the vector of $Y_2 = (y_{1j}^2, \ldots, y_{tj}^2)$ are *t* outputs produced by SDMU2; the vector of $Y_s = (y_{1j}^s, \ldots, y_{uj}^s)$ are *u* outputs produced by SDMU1 and SDMU2 together.

For analytical tractability, we use $X_{s1} = (x_{1j}^{s1}, \ldots, x_{lj}^{s1})$, $X_{s2} = (x_{1j}^{s2}, \ldots, x_{lj}^{s2})$, $Y_{s1} = (y_{1j}^{s1}, \ldots, y_{uj}^{s1})$ and $Y_{s2} = (y_{1j}^{s2}, \ldots, y_{uj}^{s2})$ to represent the shared inputs and outputs of SDMU1 and SDMU2 in each subsystem, and $X_s = X_j^{s1} + X_j^{s2}, Y_s = Y_j^{s1} + Y_j^{s2}$.

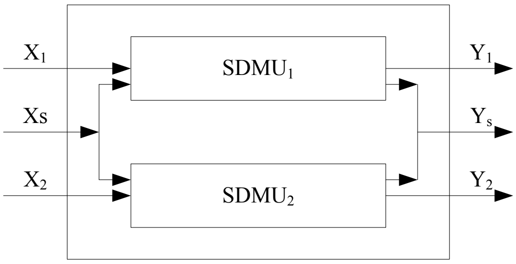

Figure 1. Parallel system structure.

In this study, we choose new product sales as independent output in Industry sub-system, the number of universities' published papers as independent output in universities sub-system. Patent applications in IU collaboration innovation system mainly come from both industry and universities subsystems; therefore the number of patent applications is seen as a shared output in the system.

According to DEA parallel production system efficiency evaluation model proposed by Kao (2009), parallel production system efficiency of the DMU under constant returns to scale (CRS) can be represented as follows:

$$\bar{\theta}^{*}_{CRS} = \min \quad \theta$$

$$s.t.$$

$$\sum_{k=1}^{2}\sum_{j=1}^{n}\lambda_j^k y_{rj}^{sk} \geq y_{ro}^{s} \quad r = 1,\ldots,u$$

$$\sum_{j=1}^{n}\lambda_j^1 y_{rj}^{1} \geq y_{ro}^{1} \quad r = 1,\ldots,s$$

$$\sum_{j=1}^{n}\lambda_j^2 y_{rj}^{2} \geq y_{ro}^{2} \quad r = 1,\ldots,t$$

$$\sum_{k=1}^{2}\sum_{j=1}^{n}\lambda_j^k x_{ij}^{sk} \leq \theta x_{io}^{s} \quad i = 1,\ldots,l$$

$$\sum_{j=1}^{n}\lambda_j^1 x_{ij}^{1} \leq \theta x_{io}^{1} \quad i = 1,\ldots,m$$

$$\sum_{j=1}^{n}\lambda_j^2 x_{ij}^{2} \leq \theta x_{io}^{2} \quad i = 1,\ldots,h$$

$$\sum_{j=1}^{n}\lambda_j^1 = \sum_{j=1}^{n}\lambda_j^2$$

$$\lambda_j^k \geq 0 \quad k = 1,2; j = 1,\ldots,n$$

The main data in this paper are all selected in the "*China Statistical Yearbook of Science and Technology*". Considering the time lag in innovation activities, we select the data in 2009 as input data and the data in 2010 as output data in this paper. This study excludes all provinces that have missing data. Finally, this study evaluates 30 observations of Chinese provinces.

Table 1 summarizes three efficiency scores under constant returns to scale (CRS), variable returns to scale (VRS) and non-increasing returns to scale (NIRS).

Table 1. Three Efficiencies of Chinese provinces.

Province	$\bar{\theta}^{*}_{CRS}$	$\bar{\theta}^{*}_{NIRS}$	$\bar{\theta}^{*}_{VRS}$
Beijing	0.5903	1.0000	1.0000
Tianjin	0.9412	1.0000	1.0000
Hebei	0.6656	0.6656	0.6692
Shanxi	0.3089	0.3089	0.3189
Inner Mongolia	0.4715	0.4715	0.4974
Liaoning	0.4605	0.4605	0.4636
Jilin	1.0000	1.0000	1.0000
Heilongjiang	0.3869	0.3869	0.3882
Shanghai	0.8232	1.0000	1.0000
Jiangsu	0.8229	1.0000	1.0000
Zhejiang	0.8769	0.8791	0.8791
Anhui	0.6534	0.6546	0.6546
Fujian	0.5968	0.5968	0.6002
Jiangxi	0.5474	0.5474	0.5491
Shandong	0.6453	1.0000	1.0000
Henan	1.0000	1.0000	1.0000
Hubei	0.6291	0.8497	0.8497
Hunan	0.6651	0.6667	0.6667
Guangdong	0.8773	1.0000	1.0000
Guangxi	0.7016	0.7016	0.7095
Hainan	0.9648	0.9648	1.0000
Chongqing	0.9698	0.9903	0.9903
Sichuan	0.4845	0.5530	0.5530
Guizhou	0.6488	0.6488	0.6661
Yunnan	0.5810	0.5810	0.6081
Shaanxi	0.6860	0.6860	0.6861
Gansu	0.8782	0.8782	0.8828
Qinghai	0.3233	0.3233	0.8972
Ningxia	0.5769	0.5769	0.6545
Xinjiang	0.7036	0.7036	0.7416

Results

The average efficiency under constant returns to scale of University- Industry collaborative innovation in China is 0.7642. However, the efficiencies of some provinces are less than the average efficiency. By the view of economic region, the efficiencies of UI collaborative innovation in eastern, northern and southern coastal China are higher than other areas in China.

Acknowledgments

The work is supported by National Natural Science Foundation of China (No. 71471091, 71271119).

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