

## Research Article

### Evaluation and Decomposition of the Innovation Efficiency in China's Agricultural and Food Products Processing Industry

Jianfeng Ma and Juanjuan Liu

Donlinks School of Economics and Management, University of Science and Technology Beijing,  
Beijing 100083, China

**Abstract:** This study attempts to evaluate the technological innovation efficiency of the agricultural and food products processing industry of China. The evaluation is based on a two-stage Data Envelopment Analysis (DEA) model with additional inputs which allows for calculating the overall efficiency and providing more specific information concerning the inefficiency of internal operation within innovation process. 12 sectors of the industry in 2011-2013 time period is selected for this study. The empirical outcomes show that the science and technology resources were not efficiently employed in most of China's agricultural and food processing sectors. This inefficiency came mainly from the inefficiency in the new product innovation activity and the significant inefficiency level in the food production sectors is a problem that should be seriously faced with in China.

**Keywords:** Agricultural and food processing industry, DEA, innovation efficiency

## INTRODUCTION

The fundamental driving force of China's modern agriculture exists in the new market demand arising from the process of industrialization and urbanization, while the fundamental way out for modern agriculture lies in the development of agricultural products processing industry (Dai and Zhang, 2013). The agricultural and food products processing industry takes the position of the traditional planting or breeding industry by playing a more and more significant roles in the growth of agricultural economy and tends to be one of the most important branches of the national economy in China. This industry is traditionally considered as a branch with low technological innovation intensity (Martinez and Briz, 2000), while new product, service, technique and scientific progress become vital instrument for the companies to satisfy the new demand of consumer and get the standing competitive power in recent years. For example, Dimitrios and Evangelos (2015) point out that the innovation capability can directly contribute to product quality and operational performance of food manufacturing companies.

From this point of view, we can reasonably understand the increase of research concerning technological innovation in agricultural and food processing industry (Menrad, 2004; Cui and Wu, 2009; Karantininis *et al.*, 2009; Gao and Li, 2014; Mohan *et al.*, 2014). More recently, Yan and Li (2015) suggests that the technological innovation has important

positive influence on the rising of industrial efficiency in food manufacturing industry. In fact, the efficiency evaluation is another active research topic in the relevant literature, such as Hoang and Alauddin (2012) evaluate and decompose the economic, environmental and ecological efficiency of OECD agriculture production; Chu (2013) analyzes the influence factors on distribution efficiency of agricultural products; Vlontzos *et al.* (2014) evaluate the energy and environmental efficiency of the primary sectors of EU member state countries. However, there are few studies concerning the efficiency evaluation of technological innovation in the agricultural and food products processing industry.

The main target of this study is to estimate the efficiency of technological innovation in China's agricultural and food products processing industry. The paper propose therefore a two-stage DEA model in which the intermediate outputs from the first stage fall into the inputs to the second stage and each stage has its respective financial and human inputs. This two-stage DEA model with additional inputs can go beyond measuring the innovation efficiency through the traditional CCR model. Specific emphasis is laid on the decomposition of overall technological innovation efficiency into new technique innovation efficiency and new product innovation efficiency, which permit revealing the internal inefficiency source of the technological innovation in China's agricultural and food products processing industry.

**Corresponding Author:** Jianfeng Ma, Donlinks School of Economics and Management, University of Science and Technology Beijing, Beijing 100083, China

This work is licensed under a Creative Commons Attribution 4.0 International License (URL: <http://creativecommons.org/licenses/by/4.0/>).

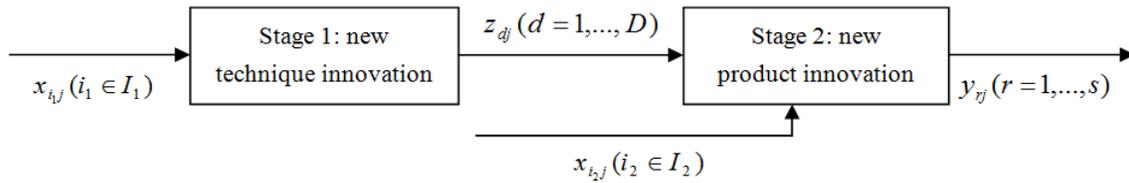


Fig. 1: Two-stage technological innovation process

**MATERIALS AND METHODS**

**Two-stage technological innovation process:** In the traditional CCR model of Charnes *et al.* (1978), the efficiency of a DMU is defined as the maximum of a ratio of the weighted sum of outputs to the weighted sum of inputs, in the condition that the same ratio for all DMUs should be less than or equal to one. The CCR model treats Decision Making Units (DMUs) as “black box” without the assumptions about its internal operations. The CCR efficiency of a process composed of several interrelated stages does not properly represent the aggregate efficiency of the sub-process. It is impossible to provide more useful information about the inefficiency within the DMUs, then to find the measures to improve the performance of sub-process which meliorate in turn the overall efficiency of DMUs. The two-stage DEA model is able to provide more useful information with insight regarding the internal source of the organization’s inefficiency.

Consider the technological innovation process of agricultural and food products processing industry as shown in Fig. 1. The process can be divided into two successive stages: New technique innovation stage and new product innovation stage.

Assume that the different sectors of the industry participate in the technological innovation process as a set of DMU indexed by  $j$  (DMU <sub>$j$</sub> :  $j = 1, \dots, n$ ) and each DMU <sub>$j$</sub> ( $j = 1, \dots, n$ ) has  $m$  inputs composed of initial inputs for the first stage denoted by  $x_{i_1j}$  ( $i_1 \in I_1$ ) and additive inputs consumed by the second stage denoted as  $x_{i_2j}$  ( $i_2 \in I_2$ ), where  $I_1 \cup I_2 = \{1, \dots, m\}$  and  $I_1 \cap I_2 = \emptyset$ . Further, suppose that each DMU <sub>$j$</sub> ( $j = 1, \dots, n$ ) has  $D$  intermediate outputs or intermediate measures (Mirhedayatian *et al.*, 2014) from the first stage denoted by  $Z_{dj}$ ( $d = 1, \dots, D$ ) and  $s$  final outputs  $y_{rj}$  ( $r = 1, \dots, s$ ) from the second stage.

**Two-stage DEA model and decomposition:** For the innovation process illustrated in Fig. 1, the efficiency scores for DMU<sub>0</sub> in the first and second stages can be calculated by the following model (1) and (2) respectively:

$$\theta_0^1 = \max \frac{\sum_{d=1}^D u_d^1 z_{d0}}{\sum_{i_1 \in I_1} v_{i_1} x_{i_10}}$$

$$\text{s.t. } \frac{\sum_{d=1}^D u_d^1 z_{dj}}{\sum_{i_1 \in I_1} v_{i_1} x_{i_1j}} \leq 1, \quad j = 1, \dots, n \tag{1}$$

$$u_d^1, v_{i_1} \geq \varepsilon, \quad d = 1, \dots, D, \quad i_1 \in I_1$$

$$\theta_0^2 = \max \frac{\sum_{r=1}^s u_r y_{r0}}{\sum_{i_2 \in I_2} v_{i_2} x_{i_20} + \sum_{d=1}^D u_d^2 z_{d0}}$$

$$\text{s.t. } \frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i_2 \in I_2} v_{i_2} x_{i_2j} + \sum_{d=1}^D u_d^2 z_{dj}} \leq 1, \quad j = 1, \dots, n \tag{2}$$

$$u_r, v_{i_2}, u_d^2 \geq \varepsilon, \quad r = 1, \dots, s, \quad i_2 \in I_2, \quad d = 1, \dots, D$$

According to the important rational assumption in Kao and Hwang (2008) and Chen *et al.* (2009), we assume that  $u_d^1 = u_d^2 = u_d$  for all  $d = 1, \dots, D$ . That is to say that the value accorded to the intermediate measures should be the same in two stages. Thus, we describe the overall efficiency of the process for DMU<sub>0</sub> as follows:

$$\theta_0 = w_1 \frac{\sum_{d=1}^D u_d z_{d0}}{\sum_{i_1 \in I_1} v_{i_1} x_{i_10}} + w_2 \frac{\sum_{r=1}^s u_r y_{r0}}{\sum_{i_2 \in I_2} v_{i_2} x_{i_20} + \sum_{d=1}^D u_d z_{d0}}$$

where,  $w_1 + w_2 = 1$ , the weight  $w_1$  and  $w_2$  are the proportion of total inputs devoted to the first and second stages respectively. These weights represent the relative contribution of each stage to the overall performance of process for DMU<sub>0</sub>.

We define:

$$w_1 = \frac{\sum_{i_1 \in I_1} v_{i_1} x_{i_10}}{\sum_{i_1 \in I_1} v_{i_1} x_{i_10} + \sum_{i_2 \in I_2} v_{i_2} x_{i_20} + \sum_{d=1}^D u_d z_{d0}} \text{ and}$$

$$w_2 = \frac{\sum_{i_2 \in I_2} v_{i_2} x_{i_20} + \sum_{d=1}^D u_d z_{d0}}{\sum_{i_1 \in I_1} v_{i_1} x_{i_10} + \sum_{i_2 \in I_2} v_{i_2} x_{i_20} + \sum_{d=1}^D u_d z_{d0}}$$

The overall efficiency of DMU<sub>0</sub> can be derived by solving the fractional program (3):

$$\theta_0 = \max \frac{\sum_{d=1}^D u_d z_{d0} + \sum_{r=1}^s u_r y_{r0}}{\sum_{i_1 \in I_1} v_{i_1} x_{i_10} + \sum_{i_2 \in I_2} v_{i_2} x_{i_20} + \sum_{d=1}^D u_d z_{d0}}$$

$$\text{s.t. } \frac{\sum_{d=1}^D u_d z_{dj}}{\sum_{i_1 \in I_1} v_{i_1} x_{i_1j}} \leq 1, \quad j = 1, \dots, n \quad (3)$$

$$\frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i_2 \in I_2} v_{i_2} x_{i_2j} + \sum_{d=1}^D u_d z_{dj}} \leq 1, \quad j = 1, \dots, n$$

$$u_d, u_r, v_{i_1}, v_{i_2} \geq \varepsilon, \quad i_1 \in I_1, \quad i_2 \in I_2, \quad r = 1, \dots, s, \quad d = 1, \dots, D$$

By applying the Charnes and Cooper (1962) transformation, the fractional program (3) can be converted to the linear model (4):

$$\theta_0 = \max \sum_{d=1}^D \pi_d z_{d0} + \sum_{r=1}^s \mu_r y_{r0}$$

$$\text{s.t. } \sum_{d=1}^D \pi_d z_{dj} - \sum_{i_1 \in I_1} \omega_{i_1} x_{i_1j} \leq 0, \quad j = 1, \dots, n$$

$$\sum_{r=1}^s \mu_r y_{rj} - \sum_{i_2 \in I_2} \omega_{i_2} x_{i_2j} - \sum_{d=1}^D \pi_d z_{dj} \leq 0, \quad j = 1, \dots, n \quad (4)$$

$$\sum_{i_1 \in I_1} \omega_{i_1} x_{i_10} + \sum_{i_2 \in I_2} \omega_{i_2} x_{i_20} + \sum_{d=1}^D \pi_d z_{d0} = 1$$

$$\pi_d, \mu_r, \omega_{i_1}, \omega_{i_2} \geq \varepsilon, \quad d = 1, \dots, D, \quad r = 1, \dots, s, \quad i_1 \in I_1, \quad i_2 \in I_2$$

The efficiency of each stage can be estimated accordingly when the optimal solution to model (4) is obtained. However, the decomposition of the overall efficiency may not be unique due to the alternative optimal solutions of the model (4). To solve this problem, we follow the approach of Kao and Hwang (2008) to find a set of multipliers which can produce the highest efficiency score of the first or second stage while maintaining the optimal overall efficiency.

If we denote the optimal value to model (4) as  $\theta_0^*$ , the optimal efficiency of the first and second stages for DMU<sub>0</sub> as  $\theta_0^{1*}$  and  $\theta_0^{2*}$  respectively, then we have the model (5) when the first stage takes priority after the Charnes and Cooper (1962) transformation:

$$\theta_0^{1*} = \max \sum_{d=1}^D \pi_d z_{d0}$$

$$\text{s.t. } \sum_{d=1}^D \pi_d z_{dj} - \sum_{i_1 \in I_1} \omega_{i_1} x_{i_1j} \leq 0, \quad j = 1, \dots, n$$

$$\sum_{r=1}^s \mu_r y_{rj} - \sum_{i_2 \in I_2} \omega_{i_2} x_{i_2j} - \sum_{d=1}^D \pi_d z_{dj} \leq 0, \quad j = 1, \dots, n$$

$$\sum_{i_1 \in I_1} \omega_{i_1} x_{i_10} = 1 \quad (5)$$

$$(1 - \theta_0^*) \sum_{d=1}^D \pi_d z_{d0} + \sum_{r=1}^s \mu_r y_{r0} = \theta_0^* (1 + \sum_{i_2 \in I_2} \omega_{i_2} x_{i_20})$$

$$\pi_d, \mu_r, \omega_{i_1}, \omega_{i_2} \geq \varepsilon, \quad d = 1, \dots, D,$$

$$r = 1, \dots, s, \quad i_1 \in I_1, \quad i_2 \in I_2$$

When we have  $\theta_0^{1*}$ , the  $\theta_0^{2*}$  can be calculated as

$$\theta_0^{2*} = \frac{\theta_0^* - w_1^* \theta_0^{1*}}{w_2^*}, \text{ where } w_1^* \text{ and } w_2^* \text{ are optimal}$$

weights obtained from model (4) which represent the portion of total inputs devoted to each stage. Similarly, we can give the second-stage pre-emptive priority while maintaining the overall efficiency at  $\theta_0^{1*}$  and calculate the optimal efficiency score of the first-stage as

$$\theta_0^1 = \frac{\theta_0^* - w_2^* \theta_0^{2*}}{w_1^*}. \text{ Note that if } \theta_0^{1*} = \theta_0^1 \text{ or}$$

$\theta_0^{2*} = \theta_0^2$  finally, we achieve unique efficiency decomposition for DMU<sub>0</sub>.

**Selection of samples and data sources:** After the presentation of materials and methods, the technological innovation efficiencies of 12 sectors in China's agricultural and food products processing industries are evaluated and decomposed by the proposed model. Considering the time lag between the inputs and outputs in innovation, we regard the full-time equivalent of researchers and the intramural expenditure on R and D in 2011 as initial inputs and the number of patent application in 2012 as intermediate measures and the full-time equivalent of application developers and the expenditure on new products development in 2012 are additional inputs for the second stage. We treat finally the sales revenue of new products in 2013 as the final outputs of the technological innovation process 2011-2013. The relevant is obtained from the China Statistical Yearbook on Science and Technology (2012-2014). The DEA models are coded using LINGO 9.0 software.

**RESULTS AND DISCUSSION**

The efficiencies calculated by the two-stage DEA model and their decomposition are reported in Table 1. The second column lists out the overall efficiency scores with their ranking, along with the efficiencies decomposition when the first stage takes priority (column 3 and 4), when the second stage takes priority (column 5 and 6) and the optimum weights for two stages (column 7 and 8).

It can be seen from Table 1 that we have unique efficiency decomposition for all sectors and only the manufacture of tobacco is relatively efficient in the whole process of technological innovation. This result indicates that the majority of China’s agricultural and food processing sectors were not efficient in using their science and technology resources in 2011-2013. In addition, the efficiency score of manufacture of tobacco far exceeds that of the second place taken by the manufacture of furniture. This shows that the government regulation industry or special monopoly sectors should possibly gain superiority in the efficiency of technological innovation.

Besides the manufacture of tobacco, the manufacture of furniture is the single sector achieving 100% efficiency in the new technique innovation stage, but none of the rest 11 sectors is efficient in the new product innovation stage and the average of the first stage efficiency scores is higher than that of the second stage. These results suggest that in general, China’s agricultural and food processing sectors tend to be relatively more efficient in converting the science and technology resources into new techniques. According to the efficiency scores for different stages, the distributions of the sectors and the efficiency decomposition are given in Fig. 2.

According to Fig. 2, we find out that three groups of sectors can be possibly delimited. The manufacture of tobacco (MTOBA) is both efficient in new technique and new product innovation stages. The four sectors

(MFUNT, MTXAA, MLFFS and PTMWB) located within the lower-right region have high new technique and low new product innovation efficiency levels. The sectors inside the lower-left area (the rest 7 sectors) get low efficiency levels in both two stages. It is noteworthy that none of the 12 sectors obtains high new product and low new technique innovation efficiency scores. This situation shows that most of China’s agricultural and food processing sectors are not efficient in the transformation of sciences and technology achievements into economic performances.

Testing Table 2, the major differences between inputs and outputs levels of three groups can be found from the global aspect. The inputs of the manufacture of tobacco are obviously less than the average inputs of the other two groups, but the final output is very important. On the contrary, the third group encompasses the sectors having the most important sciences and technology resources inputs in general, as in the case of the manufacture of textile, the manufacture of rubber and plastic for example. For the second group, the inputs levels are close to those of the first group, while the intermediate outputs level much approach to that of the third group relatively and the final output level is generally the lowest in three groups. This suggests that low efficiency level in the new product innovation is the fundamental cause for the inefficiency of the second group on the whole. As for the last group, the sciences and technology resources inputs are obviously redundant.

Finally, the sector closely related with food production, such as processing of food from agricultural products, manufacture of food, manufacture of liquor, beverages and refined tea, are most inefficient sectors. This shows that China’s food production sectors face insufficient innovation motive power with a huge internal market and this may be a severe problem for the future development of China’s agricultural and food products processing industry.

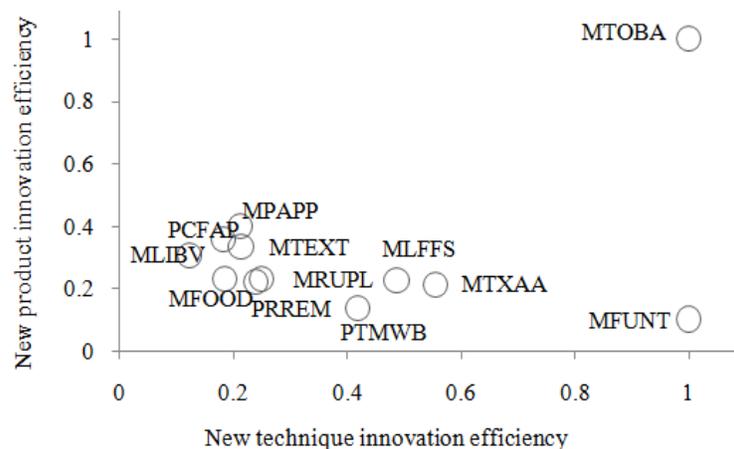


Fig. 2: Efficiency decomposition and sectors distribution

Table 1: Technological innovation efficiency scores and decomposition of 12 sectors

Industries	$\theta_0$	$\theta_0^{1*}$	$\theta_0^2$	$\theta_0^1$	$\theta_0^{2*}$	$W_1$	$W_2$
Processing of food from agricultural products (PCFAP)	0.2086 (10)	0.1819	0.3554	0.1819	0.3554	0.8461	0.1539
Manufacture of food (MFOOD)	0.1918 (11)	0.1846	0.2310	0.1846	0.2310	0.8442	0.1558
Manufacture of liquor, beverages and refined tea (MLIBV)	0.1436 (12)	0.1237	0.3044	0.1237	0.3044	0.8899	0.1101
Manufacture of tobacco (MTOBA)	1.0000 (1)	1.0000	1.0000	1.0000	1.0000	0.1178	0.8822
Manufacture of textile (MTEXT)	0.2349 (9)	0.2139	0.3331	0.2139	0.3331	0.8238	0.1762
Manufacture of textile, apparel and accessories (MTXAA)	0.4330 (3)	0.5566	0.2110	0.5566	0.2110	0.6424	0.3576
Manufacture of leather, fur, feather and related products and shoes (MLFFS)	0.4018 (4)	0.4875	0.2260	0.4875	0.2260	0.6723	0.3277
Processing of timbers and manufacture of wood, bamboo, rattan, palm and straw (PTMWB)	0.3355 (5)	0.4188	0.1366	0.4188	0.1366	0.7048	0.2952
Manufacture of furniture (MFUNT)	0.5499 (2)	1.0000	0.0998	1.0000	0.0998	0.5000	0.5000
Manufacture of paper and paper products (MPAPP)	0.2448 (7)	0.2122	0.3985	0.2122	0.3985	0.8250	0.1750
Printing, reproduction of recording media (PRREM)	0.2363 (8)	0.2402	0.2201	0.2402	0.2201	0.8063	0.1937
Manufacture of rubber and plastic (MRUPL)	0.2453 (6)	0.2491	0.2300	0.2491	0.2300	0.8006	0.1994
Average	0.3521	0.4057	0.3122	0.4057	0.3122	0.7061	0.2939

Table 2: The average of inputs and outputs for three groups of sectors

	High efficiency levels in both two stages	High first and low second stage efficiency levels	Low efficiency levels in both two stages
Full time equivalent of researchers	1946	2370	7443
Internal expenditure on R&D	159702	169748	815303
Expenditure on new product development	152354	381627	1164251
Full time equivalent of application developers	1864	11119	22548
Patent application	1581	4134	6355
Sales revenue of new products	15913130	7355476	18790609

### CONCLUSION

This study evaluated the technological innovation efficiency in China's agricultural and food products processing industry by developing a two-stage DEA model. This new approach allows to open the "black box" of the innovation process and to identify specific sources of inefficiency within the internal structure. The results show that: first, the monopoly sector with policy protection was the most efficient in technological innovation, but it could not represent the general technological innovation circumstance. Second, the mean value of the overall and sub stage's efficiency scores did not reach 0.5 and the score gaps between the efficient and inefficient sectors were relatively important, this means that the most of China's agricultural and food processing sectors could not efficiently make use of the science and technology resources. Third, the efficiency scores of new product innovation stage were relatively low that of new technique innovation stage in general, that is to say, the sources of technological innovation inefficiency lies in the new product innovation process in most of the case. And finally, the lowest efficiency scores were found in three food production sectors and this suggests that the relatively low demand elasticity has negative effect on the sector innovation efficiency in China. The efforts to improve the technological innovation performance of China's agricultural and food products processing

industry should be therefore made primarily in reducing the efficiency scores gaps, increasing the new product innovation performance and paying attention into the technological innovation inefficiency in the food production sectors.

### ACKNOWLEDGMENT

This research is supported by Key projects on strategic research of Ministry of Education of China (KJW-A-1410) and National Natural Science Foundation of China (71471015).

### REFERENCES

- Charnes, A. and W.W. Cooper, 1962. Programming with linear fractional functionals. *Nav. Res. Logist. Q.*, 9: 181-186.
- Charnes, A., W.W. Cooper and E. Rhodes, 1978. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.*, 2(6): 429-444.
- Chen, Y., W.D. Cook, N. Li and J. Zhu, 2009. Additive efficiency decomposition in two-stage DEA. *Eur. J. Oper. Res.*, 196: 1170-1176.
- Chu, Y., 2013. Quantitative analysis of influence factors on distribution efficiency of agricultural products: A case study using data envelopment analysis. *Adv. J. Food Sci. Technol.*, 5(12): 1669-1673.

- Cui, C. and L. Wu, 2009. Technological innovation ability of agricultural products processing industry in China. *Trans. Chinese Soc. Agr. Eng.*, 25(3): 303-307.
- Dai, X. and D. Zhang, 2013. Perspective of Chinese agro-products processing industry from agricultural modernization. *J. Chinese Inst. Food Sci. Technol.*, 13(5): 6-10.
- Dimitrios, K. and P. Evangelos, 2015. The impact of innovation capability on the performance of manufacturing companies the Greek case. *J. Manuf. Technol. Manage.*, 26(1): 104-130.
- Gao, S. and D. Li, 2014. Spatial analysis of agricultural production technical efficiency: Through DEA in Mianyang city. *Int. J. Technol. Policy Manage.*, 14(2): 193-203.
- Hoang, V.N. and M. Alauddin, 2012. Input-orientated data envelopment analysis framework for measuring and decomposing economic, environmental and ecological efficiency: An application to OECD agriculture. *Environ. Resour. Econ.*, 51(3): 431-452.
- Kao, C. and S.N. Hwang, 2008. Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan. *Eur. J. Oper. Res.*, 185: 418-429.
- Karantininis, K., J. Sauer and W.H. Furtan, 2009. Innovation and integration in the agri-food industry. *Food Policy*, 35: 112-120.
- Martinez, M.G. and J. Briz, 2000. Innovation in the Spanish food and drink industry. *Int. Food Agribus. Manage. Rev.*, 3: 155-176.
- Menrad, K., 2004. Innovations in the food industry in Germany. *Res. Policy*, 33: 845-878.
- Mirhedayatian, S.M., M. Azadi and R. Farzipoor Saen, 2014. A novel network data envelopment analysis model for evaluating green supply chain management. *Int. J. Prod. Econ.*, 147(Part B): 544-554.
- Mohan, G., H. Matsuda, S.A. Donkoh, V. Lolig and G.D. Abbeam, 2014. Effects of research and development expenditure and climate variability on agricultural productivity growth in Ghana. *J. Disaster Res.*, 9(4): 443-451.
- Vlontzos, G., S. Niavis and B. Manos, 2014. A DEA approach for estimating the agricultural energy and environmental efficiency of EU countries. *Renew. Sust. Energ. Rev.*, 40: 91-96.
- Yan, X. and X. Li, 2015. The impact of technological innovation on industrial efficiency and food manufacturing industry. *Adv. J. Food Sci. Technol.*, 7(5): 368-373.