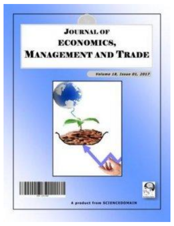

Journal of Economics, Management and Trade

21(9): 1-14, 2018; Article no.JEMT.44053
ISSN: 2456-9216
(Past name: British Journal of Economics, Management & Trade, Past ISSN: 2278-098X)

Comparisons on Science and Technology Innovation Efficiency between Large-sized and Medium-sized Industrial Enterprises in China: Based on DEA Method and Equal Part Linear Regression

Qiu-Lin Wu[1*] and Wen-Tsao Pan[1]

[1]*School of Business, Guangdong University of Foreign Studies, Guangzhou, China.*

Authors' contributions

This work was carried out in collaboration between both authors. Author QLW designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Author WTP managed the analyses of the study and the literature searches. Both authors read and approved the final manuscript.

Article Information

DOI: 10.9734/JEMT/2018/44053
Editor(s):
(1) Dr. Polona Tominc, Professor, Department of Quantitative Economic Analysis, University of Maribor, Slovenia.
Reviewers:
(1) Lawrence Okoye, University of Maiduguri, Nigeria.
(2) Husein Mohamed Irbad, Lincoln University College, Malaysia.
(3) Y. U. Xiaobao, Shanghai University of Electric Power, China.
(4) Jackson Akpojaro, University of Africa, Toru-Orua, Nigeria.
Complete Peer review History: http://www.sciencedomain.org/review-history/26456

Original Research Article

Received 07 July 2018
Accepted 16 September 2018
Published 30 September 2018

ABSTRACT

This paper constructs an evaluation system for science and technology efficiency of industrial enterprises based on existing research achievements, and implements a comparative analysis on the innovation efficiency of large and medium-sized industrial enterprises by data envelopment analysis (DEA). Further, it discusses the factors influencing the science and technology innovation efficiency of large and medium-sized industrial enterprises by equal part linear regression. The results show that: firstly, the innovation efficiency of large-sized enterprises is equivalent to that of medium-sized ones overall, but both possess their unique advantages in various subdivided industries. Secondly, most of the large-sized and medium-sized industrial enterprises show

**Corresponding author: E-mail: wuqiulin2016@qq.com;*

constant or diminishing returns to scale. Thirdly, in the mining and manufacturing industries, both large and medium-sized enterprises show the highest input redundancy and obvious output insufficiency. Finally, there are different factors influencing the science and technology innovation efficiency of large and medium-sized industrial enterprises.

Keywords: Large and medium-sized industrial enterprises; science and technology efficiency; data envelopment analysis (DEA); equal part linear regression.

1. INTRODUCTION

In recent years, the enterprises in various industries have paid more and more attention to science and technology innovation and continuously increased the research and development investment. However, some enterprises increased the R&D income without considering efficiency. Unreasonable input structure can by no means effectively promote the progress of science and technology innovation. Industry aggradation maintains a hotspot topic during recent years in China, so it is essential to explore a reasonable allocation of resources to improve the technical innovation.

Some scholars have already acquired important achievements regarding the research on enterprise innovation. Zhao et al. [1] evaluated the innovation performances of 151 high-tech enterprises in Jilin Province, China, based on the DEA method with real-time investigation data. Xiong et al. [2] measured the operation performances of high-tech enterprises in China by adding intangible output, brand assets; Hung and Wang [3] respectively evaluated the innovation efficiency of high-tech enterprises and that of enterprises in traditional industries; Romijn [4] researched the innovation efficiency of high-tech industries by multiple regression model. Besides, many scholars have analysed enterprises with different volumes within the same industry, such as measured and compared the innovation efficiency of large with medium-sized high-tech enterprises [5], or medium with small-sized high-tech enterprises [6], or large with medium-sized industrial enterprises [7,8]. There are also some researchers paying attention to the science and technology innovation around the word [9,10], or focus on science and technology innovation of different kinds of parks [11,12].

The above-mentioned literature indicate mainly four defects in existing researches: first, certain existing researches mainly focus on the innovation efficiency of high-tech enterprises instead of traditional enterprises. The economic development of a country cannot be achieved without the joint progress of various industries, thus more attention should be paid to the innovation efficiency of traditional enterprises to help them regain vitality. Second, as to the construction of the evaluation system, most researches ignored the cost of new technology introduction and learning. In the innovation process, not all the innovations originate from within an enterprise, it may also purchase and introduce new technologies, thus the cost of new technology introduction and learning should be taken into account. Meanwhile, reputation, as an intangible asset, also has a profound and lasting influence on enterprises development, which shall not be neglected in the construction of efficiency evaluation system. Third, the existing researches on the innovation efficiency of enterprise only focused on the evaluation system construction and the efficiency measurement without further discussing the main factors influencing the innovation efficiency of enterprises. Fourth, although there are already researches measuring the innovation efficiency of large and medium-sized enterprises, large and medium-sized enterprises differ in many aspects, such as manpower, materials and finance condition, management experience and state support, thus their innovation efficiency and influencing factors will surely be different.

Therefore, this paper is designed to compare the innovation efficiency of Chinese large-sized and medium-sized enterprises by DEA method. The following contents are: firstly, constructing an efficiency evaluation index system for industrial enterprises based on existing researches and select proper DEA evaluation model. Secondly, analysing and comparing the innovation efficiency of large-sized enterprises and medium-sized ones. Finally, exploring different factors that are influencing the innovation efficiency of large and medium enterprises by the equal part linear regression.

2. CONSTRUCTION OF EVALUATION SYSTEM AND DEA MODEL INTRODUCTION

2.1 Evaluation Index System

The innovation efficiency evaluation system of enterprise includes two aspects, namely innovation input and output. In previous studies, the first-class indicators of innovation input are manpower and finance input for science and technology innovation, and the first-class output indicators involve the benefit of new technologies (number of patent applications) and new products (such as the sales profits). In this paper, innovation input indicators are divided into manpower input, research investment input, management expense input, technology introduction expense and expense on the absorption of technologies introduced. Innovation output indicators include the number of patent applications, the number of effective invention patents, and the number of established national and industrial standards, the number of registered trademarks and sales income of new products. Various indexes are summarised in Table 1 as follows.

Table 1. Science and technology innovation efficiency evaluation system of industrial enterprise

Grade-I indexes	Grade-II indexes	Explanations on grade-II indexes
Innovation input	Manpower input (person)	Aggregation of the number of enterprise's domestic staff and that of researchers of relevant research institutions
	Research investment input (10,000 yuan)	Aggregation of enterprise's domestic investment expenditure and the investment expenditure of relevant research institutions
	Management expense input (10,000 yuan)	Labor costs on enterprise's research and development activities
	Technology introduction input (10,000 yuan)	Expenses on enterprise's introduction of technologies from foreign countries, Hongkang, Macao and Taiwan and domestic innovative technologies
	Expense on absorption of technologies introduced (10,000 yuan)	Aggregation of the expenditure for learning and comprehension of technologies introduced by enterprise's researchers and the expense on transformation of technologies introduced
Innovation output	Number of patent applications (item)	The number of patent applications proposed by enterprise as the first applicant to foreign and domestic administrative departments in charge of intellectual property rights and handled by such departments.
	Number of effective invention patents (item)	The number of validly existing invention patents possessed by enterprise as the first patentee and authorised by foreign and domestic administrative departments in charge of intellectual property rights
	Number of established national and industrial standards (item)	The number of national or industrial standards formed on the basis of independent research and development or proprietary intellectual property rights of enterprise which have been approved by relevant departments
	Number of registered trademarks (item)	The number of validly existing trademarks possessed by enterprise as the first trademark registrant and approved to be registered by foreign and domestic administrative departments in charge of trademarks
	Sales income of new products (10,000 yuan)	The sales amount of products designed and produced by innovative technologies

2.2 Evaluation Model

It can be seen from the science and technology innovation efficiency evaluation system of industrial enterprises that enterprise innovation is a complex system featured by multiple inputs and outputs so that the data envelopment analysis (DEA) is needed. DEA includes two basic modes, namely the CCR model based on constant returns to scale and BCC model based on variable returns to scale. The essence of science and technology innovation of enterprises lies in the production and use of innovative knowledge. Knowledge possesses such features as sustainable dissemination and continued derivation of new, so the output-oriented DEA-BCC model is chosen.

Proposing that there are n decision-making units (DMU) to be analysed, marked as DMU_j (j=1, 2, 3,…, n); each DMU possess m kinds of inputs, marked as xi (i=1, 2, 3,…, m), with the weight of each kind of input and the total inputs respectively marked as vi and V; each DMU possess q kinds of outputs, marked as yr (i=1, 2, 3,…, q), with the weight of each kind of output and the total outputs respectively marked as ur and U, and the output-input ratio (namely efficiency) of DMU_k can be expressed as Formula (1). In this formula, U_k and V_k are the amount of output and input of DMU_k respectively.

$$U_k = \sum_{r=1}^{q} u_r \, y_{rk}$$

$$V_k = \sum_{i=1}^{m} v_i \, x_{ik}$$

$$h_i = \frac{U_k}{V_k}$$

$$\mathrm{u}, \mathrm{v} \geq 0$$

The dual programming formula (including envelopment model) of output-oriented BCC model is expressed as Formula (2):

$$\min \theta$$

$$\mathrm{s.t.} \sum_{k=1}^{n} \lambda_k \, x_k + s^- = \theta x_0$$

$$\sum_{k=1}^{n} \lambda_k \, y_k - s^+ = y_0$$

$$\sum_{k=1}^{n} \lambda_k = 1$$

$$\lambda_k \geq 0, k = 1,2, \ldots, n$$

$$\theta \in (-\infty, +\infty), s^- \geq 0, s^+ \geq 0$$

In Formula (2), s^+ and s^- are respectively the slack variable (economic meaning: output insufficiency of the corresponding index) and residual variable (economic meaning: output redundancy of the corresponding index) introduced based on the dual form of CCR model, and then we can evaluate the input-output efficiency simply through figuring out the optimal solutions of θ^0、λ^0、s^{0+}、s^{0-} in the formula. After that, through further introducing the bound variable ($\sum_{k=1}^{n} \lambda_k = 1$) into the formula, we can interpret the overall efficiency in a more comprehensive way from such perspectives as pure technical efficiency and scale efficiency, thus judging the specific state of DMU, namely being under increasing returns to scale or diminishing returns to scale or maintains constant.

3. EMPIRICAL RESEARCH

3.1 Data Source

The data adopted in the paper comes from Statistical Yearbook of Science and Technology Activities of Industrial Enterprises (2016) which collects the data from 40 industries. To be specific, the mining industry includes 6 subdivided industries, namely coal mining and washing, oil and gas exploration, ferrous metal ore mining, non-ferrous metal ore mining and non-metallic ore mining; the manufacturing industry has 28 subdivided industries, namely, farm and sideline food processing, food manufacturing, wine, beverages and refined tea manufacturing, tobacco products and textile; other industrial types have 6 subdivided industries, they are comprehensive utilisation of waste resources, metal products and machinery and equipment maintenance, electricity, heat and gas and water production and supply, electricity and heat production and supply, gas production and supply and water production and supply.

3.2 Efficiency Evaluation and Analysis of Returns to Scale

DEAP 2.1 software is used to measure the science and technology innovation efficiency of enterprises from 40 sample industries figuring out the overall efficiency, pure technical efficiency, scale efficiency and returns to scale as well as the redundancy of various input indexes and the insufficiency of output indexes of every industry. Considering a large number of samples, the paper would just analyse the summary of the results from four aspects, namely DEA efficiency, returns to scale, input redundancy and output insufficiency, as shown in Table 2 and Table 3.

Strong DEA efficiency means both pure technical efficiency and scale efficiency are 1 (namely the overall efficiency is 1), weak DEA efficiency means either pure technology efficiency or scale efficiency is 1, and non-DEA efficiency indicates the situation in which neither pure technology efficiency nor scale efficiency is 1. It can be seen from Tables 2 and 3 that the innovation efficiency of large-sized enterprises is slightly better in terms of strong DEA efficiency. In the mining industry, large-sized industrial enterprises have higher innovation efficiency in the non-metallic ore mining industry. In the manufacturing industry, large-sized industry enterprises have higher innovation efficiency in three industrial types, namely textile, textile clothing and costume, leather and fur as well as feather and feather product industries. However, medium-sized industrial enterprises have a higher innovation efficiency in the following five industrial types: oil processing and coking and nuclear fuel processing, pharmaceutical manufacturing, chemical raw materials and chemical manufacturing, nonferrous metal smelting and rolling processing, and the industry manufacturing railways and ships, aerospace equipment and other transport equipment. In other industrial types, large-sized industrial enterprises have higher innovation efficiency in water production and supply industry, while the innovation efficiency of medium-sized industrial enterprises is higher in gas production and supply industry.

All weak DEA efficiency results in this paper belong to technology efficiency, while corresponding scale efficiency is invalid, showing that the management on innovation activities in both large and medium-sized industrial enterprises in China is becoming mature, and these enterprises can well master the demands on input elements, but still fails to achieve scale efficiency in a comprehensive way. Tables 2 and 3 show that neither large nor medium-sized industrial enterprises show weak DEA efficiency in science and technology innovation, instead, they show non-DEA efficiency respectively in 2 and 3 subdivided industries, reflecting that a large difference in innovation capacity exists between various subdivided industries in terms of both large and medium-sized enterprises. In the manufacturing industry, there are 11 large-sized and 2 medium-sized enterprises industrial enterprises belong to non-DEA efficiency. In other industrial types, large-sized industrial enterprises show weak DEA efficiency in 2 subdivided industries (electricity, heat and gas production and supply industry and water production and supply industry) without showing any non-DEA efficiency, while medium-sized industrial enterprises show non-DEA efficiency in 2 subdivided industries (electricity, heat and gas production and supply industry and water production and supply industry) without showing any weak DEA efficiency, proving that large-sized industrial enterprises show higher innovation efficiency in other industrial types.

Regarding returns to scale, the innovation efficiency of large-sized enterprises and medium-sized enterprises are similar. The percentage of industries with constant returns to scale is 50% for both large and medium-sized enterprises. While 37.5% industries belong to large-sized enterprises and 40% industries belong to medium-sized enterprises are diminishing returns, showing that the innovation technologies adopted by large and medium enterprises in China are relatively mature with limited improvement space. The percentage of industries with increasing returns to scale is 12.5% and 10% respectively, reflecting that there are still a minority of enterprises in their growth period. Overall, seeing from the number of industries regarding DEA efficiency and returns to scale, large and medium-sized enterprises differ slightly, but both have their respective advantages in specific subdivided industries.

3.3 Analysis on Input Redundancy and Output Insufficiency

Tables 4 and 5 show the result of input redundancy and output insufficiency of large and medium-sized industrial enterprises respectively, wherein x1 (p1) - x5 (p5) respectively indicate manpower input, research investment input, technology introduction expense, management expense and expense on absorption of technologies adopted, and y1 (q1) - y5 (q5) respectively indicates the number of patent applications, the number of effective invention patents, the number of established national and

Table 2. Summary of innovation efficiency evaluation for large-sized enterprises

Industries	Number of subdivided industries	Strong DEA efficiency (number)	Weak DEA efficiency (number)	Non- DEA efficiency (number)	Returns to scale (number)		
					Increasing	Diminishing	Constant
Mining industry	6	4	0	2	0	1	5
Manufacturing industry	28	11	6	11	4	13	11
Other types	6	4	2	0	1	1	4
Total	40	19 (47.5%)	8 (20%)	13 (32.5%)	5 (12.5%)	15 (37.5%)	20 (50%)

Table 3. Summary of innovation efficiency evaluation for medium-sized enterprises

Industries	Number of subdivided industries	Strong DEA efficiency (number)	Weak DEA efficiency (number)	Non- DEA efficiency (number)	Returns to scale (number)		
					Increasing	Diminishing	Constant
Mining industry	6	3	0	3	1	2	3
Manufacturing industry	28	13	6	9	2	13	13
Other types	6	4	0	2	1	1	4
Total	40	20 (50%)	6 (15%)	14 (35%)	4 (10%)	16 (40%)	20 (50%)

industrial standards, the number of registered trademarks and sales income of new products. In the tables, "number: zero" indicates the inexistence of DMUs with input redundancy or output insufficiency, while "non-zero number" indicates the number of DMUs with input redundancy or output insufficiency.

Comparing the results in Table 4 and Table 5, we can find that only in the manufacturing industry the overall input redundancy degree of large-sized industrial enterprises is higher than that of medium-sized ones, while in other industries, the overall input redundancy degree of the both are low and almost the same. To be specific, in the manufacturing industry, research investment input (x2 and p2), management expense (x4 and p4) and expense on the absorption of technologies introduced (x5 and p5) have the highest redundancy degree. Although the output insufficiency degree of large-sized industrial enterprises in the number of patent applications (y1) within the manufacturing industry is higher than that of medium-sized industrial enterprises, the output efficiency of innovation activities of large-sized industrial enterprises is higher overall.

3.4 Equal Part Linear Regression against Factors Influencing Innovation Efficiency

To further discuss the factors influencing innovation efficiency, the paper respectively analyses the environment influencing factors of 40 industry samples by adopting equal part linear regression proposed by Scholar Pan in 2107 [13]. Compared to the linear regression, the equal part linear regression works very well in solving the data with abnormal distribution condition, and this model is much easier than the model of quantile regression. Meanwhile, it is clear that the influences of each level of the independent variable are on the dependent variable. Different from other analysis methods, equal part linear regression divides the whole samples into n parts (n is determined according to researchers' demands), making it possible to see the significance and overvaluation or undervaluation of independent variables at different division parts, so that we can judge the influence of independent variables on dependent variables more effectively. In the research implemented in this paper, the innovation efficiency figured out by DEA model is adopted as the dependent variable, tax calculated and deducted with regard to research and development expenses, tax deducted for high-tech enterprises, the number of doctors and masters and capital of government and enterprises are adopted as independent variables. The setup of variables for equal part linear regression is shown in Table 6, and the analysed results are shown in Tables 7 and 8 and Figs. 1 and 2.

Table 7 shows the results of an equal part linear regression of large-sized industrial enterprises. The model is divided into four equal parts in this study, and it can be seen from the table whether there existany difference between the four subdivided models. The value of p lower than 0.1 indicates the existence of such difference, which means the adoption of general linear regression analysis methods may result in overvaluation or undervaluation on the acting effect of independent variables on independent variables, namely there may exist a difference between input elements and corresponding output in different quantiles. It can be seen from Table 7 that in the case of large-sized industrial enterprises, a marked difference exists in tax deducted for high-tech enterprises (n2, $p<0.01$) and enterprise capital (n6, $p<0.05$) between the first and second equally divided parts, in the number of masters (n4, $p<0.05$), government capital (n5, $p<0.01$) and enterprise capital (n6, $p<0.01$) between the first and third equally divided parts, in tax calculated and deducted with regard to research and development expenses (n1, $p<0.01$) and number of doctors (n3, $p<0.01$) between the first and fourth equally divided parts, in tax calculated and deducted with regard to research and development expenses (n1, $p<0.01$), tax deducted for high-tech enterprises (n2, $p<0.05$), number of masters (n4, $p<0.01$), government capital (n5, $p<0.01$) and enterprise capital (n6, $p<0.05$) between the second and third equally distributed parts, in tax calculated and deducted with regard to research and development expenses (n1, $p<0.01$), tax deducted for high-tech enterprises (n2, $p<0.01$), number of doctors (n3, $p<0.01$), government capital (n5, $p<0.05$) and enterprise capital (n6, $p<0.01$) between the second and fourth equally distributed parts, and in tax deducted for high-tech enterprises (n2, $p<0.1$), number of doctors (n4, $p<0.01$), number of masters (n4, $p<0.01$), government capital (n5, $p<0.01$) and enterprise capital (n6, $p<0.1$) between the third and fourth equally divided parts.

Table 4. Summary of input redundancy and output insufficiency results

Industries		Input redundancy					Output insufficiency				
		x1	x2	x3	x4	x5	y1	y2	y3	y4	y5
Mining industry	Number: zero	5	5	5	4	6	5	6	6	4	6
	Non-zero number	1	1	1	2	0	1	0	0	2	0
	Total	6									
Manufacturing industry	Number: zero	26	17	22	20	22	17	21	28	20	28
	Non-zero number	2	11	6	8	6	11	7	0	8	0
	Total	28									
Others	Number: zero	6	6	6	6	6	6	6	6	6	6
	Non-zero number	0	0	0	0	0	0	0	0	0	0
	Total	6									

Table 5. Summary of input redundancy and output insufficiency results

Industries		Input redundancy					Output insufficiency				
		p1	p2	p3	p4	p5	q1	q2	q3	q4	q5
Mining industry	Number: zero	4	5	6	3	3	3	5	4	3	5
	Non-zero number	2	1	0	3	3	3	1	2	3	1
	Total	6									
Manufacturing industry	Number: zero	23	22	25	23	23	22	22	23	21	28
	Non-zero number	5	6	3	5	5	6	6	5	7	0
	Total	28									
Others	Number: zero	5	4	5	5	5	5	6	4	4	5
	Non-zero number	1	2	1	1	1	1	0	2	2	1
	Total	6									

Table 6. Equal part linear regression model

Grade-I indexes	Grade-II indexes	Grade-III indexes	Explanations on Grade-III indexes
Environmental influencing factors	Government's tax policy support	Tax calculated and deducted with regard to research and development expenses	The income tax in relation to research and development expenses calculated and deducted before tax payment by enterprise in accordance with the provisions of relevant policies and tax laws
		Tax deducted for high-tech enterprises	The amount of enterprise's income tax deducted legally according to relevant policies of our country
	Education background structure of researchers	Number of doctors	Number of persons with doctoral degree in relevant research and development institutions
		Number of masters	Number of persons with master degree in relevant research and development institutions
	Source of research and development capital	Government capital	Research and development capital originating from governments at all levels
		Enterprise capital	Research and development capital originating from the enterprise or other enterprises
Enterprise's innovation efficiency	Enterprise's innovation efficiency	Enterprise's innovation efficiency	Overall innovation efficiency measured by DEA model

Table 7. Results of equal part linear regression of large-sized enterprises

Comparisons between equally divided models	Variables	F value	Sig.	Comparisons between equally divided models	Variables	F value	Sig.
Model 1 and 2	n1	0.381	-	Model 2 and 3	n1	0.028	***
	n2	0.0317	***		n2	0.231	**
	n3	0.512	-		n3	0.624	-
	n4	1.179	-		n4	0.136	***
	n5	1.982	-		n5	0.045	***
	n6	0.204	**		n6	0.214	**
Model 1 and 3	n1	0.011	-	Model 2 and 4	n1	0.028	***
	n2	0.007	-		n2	0.070	***
	n3	0.320	-		n3	0.081	***
	n4	0.161	**		n4	0.006	-
	n5	0.091	***		n5	0.001	**
	n6	0.043	***		n6	0.056	***
Model 1 and 4	n1	0.011	***	Model 3 and 4	n1	0.976	-
	n2	0.002	-		n2	0.302	*
	n3	0.042	***		n3	0.131	***
	n4	0.007	-		n4	0.048	***
	n5	0.002	-		n5	0.030	***
	n6	0.011	-		n6	0.262	*

*Note: - Indicates being less obvious, * Indicates p<0.1, ** Indicates p<0.05, and *** Indicates p<0.01*

Table 8. Results of equal part linear regression of medium-sized enterprises

Comparisons between equally divided models	Independent variables	F value	Sig.	Comparisons between equally divided models	Independent variables	F value	Sig.
Model 1 and 2	m1	67.855	***	Model 2 and 3	m1	30.939	***
	m2	3.973	-		m2	3.254	-
	m3	3.956	-		m3	9.133	*
	m4	7.795	*		m4	8.952	*
	m5	0.663	-		m5	160.371	***
	m6	68.951	***		m6	4.139	-
Model 1 and 3	m1	2099.419	-	Model 2 and 4	m1	281.333	***
	m2	12.931	**		m2	720.072	***
	m3	36.134	***		m3	32.095	***
	m4	69.781	***		m4	175.962	***
	m5	106.340	***		m5	19367.722	-
	m6	285.423	***		m6	15.427	**
Model 1 and 4	m1	19089.906	-	Model 3 and 4	m1	9.092	*
	m2	2861.475	-		m2	221.277	***
	m3	126.971	***		m3	3.513	-
	m4	1371.631	***		m4	19.655	**
	m5	12842.573	-		m5	120.768	***
	m6	1063.719	-		m6	3.726	-

*Note: - Indicates being less obvious, * Indicates $p<0.1$, ** Indicates $p<0.05$, and *** Indicates $p<0.01$*

In Figs. 1 and 2, the grey area indicates a 95% confidence interval, the red line indicates the acting effect of independent variables on dependent variables in times of data analysis by simple linear regression (a nearly flat straight line), the black line indicates the acting effect of independent variables on dependent variables in times of data analysis by equal part linear regression, through which the overvaluation or undervaluation of the acting effect in various equally divided parts can be seen. Fig. 1 shows that the tax calculated and deducted with regard to research and development expenses (n1) is undervalued in the first and fourth equally distributed parts, showing that the lower or higher level deduction of the tax calculated and deducted with regard to research and development expenses has a larger influence on the innovation efficiency for large-sized industrial enterprises than the medium-level deduction. Similarly, the tax deducted for high-tech enterprises (n2) is overvalued in the fourth equally distributed part, meaning that when the deduction level of the tax deducted for high-tech enterprises exceeds a certain threshold value, it fails to promote the innovation efficiency of large-sized industrial enterprises, for which the reason may be that excessively high level of the tax deducted for high-tech enterprises may make enterprises slack off, thus reducing its influence on innovation efficiency; the number of doctors (n3) is slightly undervalued in the first and second equally divided parts, reflecting that during the gradual increase in the number of researchers with doctoral degree, when the number increases to a certain level, subsequent substantial increase of the number fails to increase the innovation efficiency of large-sized industrial enterprises correspondingly. The number of masters (n4) is slightly overvalued in the first and fourth equally divided parts, while undervalued in the second equally divided part, meaning that neither excessively small nor large number of researchers has obvious promotion to the innovation efficiency of large-sized industrial enterprises. Only when the number maintains at the medium level, can it obviously increase the innovation efficiency. Government capital (n5) is slightly undervalued in the first equally divided part, proving that the supply of a small quantity of research and development capital support by the government has a relatively large influence on the increase of innovation efficiency. Enterprise capital (n6) is slightly undervalued in the fourth equally divided part, disclosing that the larger the quantity of capital originating from enterprises is, the greater its effect on the increase of innovation efficiency. This may be due to enterprises typically run for profits, larger quantity of capital originating from enterprises requires larger amount of income, only so can enterprises gain profits, the acting effect of which is right contrary to that of government's supporting capital.

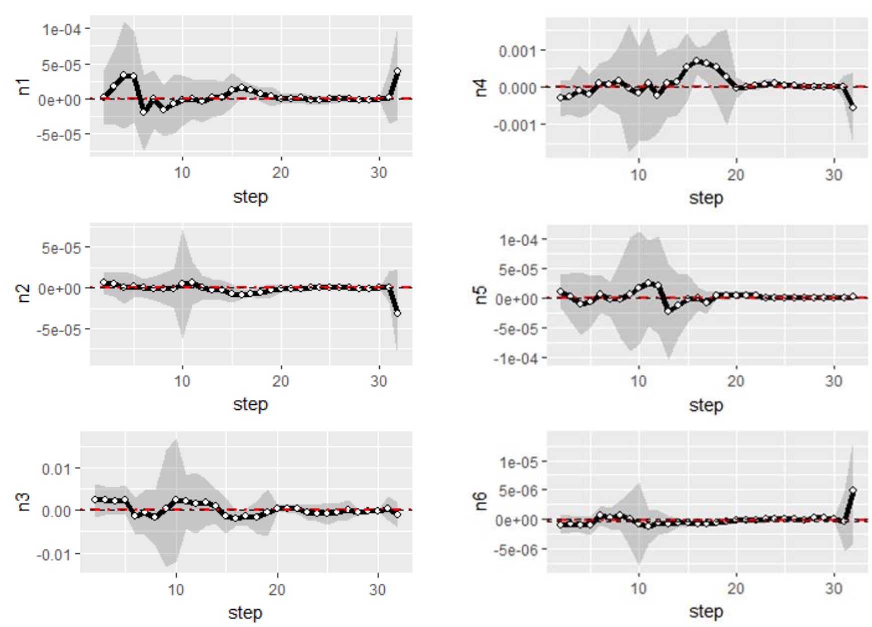

Fig. 1. Factors influencing the innovation efficiency of large-sized enterprises

Table 8 and Fig. 2 show the results gained based on the analysis of data regarding medium-sized industrial enterprises by the method of equal part linear regression. Being similar with that adopted for large-sized industrial enterprises, the analysis result figuring out whether there exists any difference between various variables in every equally divided part will not be detailed here once again. The paper will mainly interpret the results in Fig. 2. It can be seen from Fig. 2 that the tax calculated and deducted with regard to research and development expenses (m1) is undervalued in the first and fourth equally distributed parts, which is similar to that of large-sized industrial enterprises. The undervaluation degree here is lower, showing that the lower or high-level deduction of the tax calculated and deducted with regard to research and development expenses has a larger influence on the innovation efficiency of medium-sized industrial enterprises than the medium-level deduction. Being different from large-sized industrial enterprises, the tax deducted for high-tech enterprises (m2) is lightly undervalued in the first equally divided part but overvalued in the second equally divided part. This indicates that the low-level tax deduction can obviously increase the innovation efficiency of medium-sized industrial enterprises. The number of doctors (m3) is lightly overvalued in the fourth equally divided part, for which the reason may be that other resources of medium-sized enterprises are limited, thus making even the possession of a large quantity of researchers with doctoral degree fail to obviously increase its innovation efficiency. The number of masters (m4) is undervalued in the fourth equally divided part, reflecting that larger number of researchers with master degree can play a larger promotion role to the innovation efficiency of medium-sized industrial enterprises, which is different from large-sized industrial enterprises. The Government capital (m5) is undervalued in the first and fourth equally divided parts, reflecting that the supply of either small or large quantity of capital support by government has a large influence on the increase of innovation efficiency. The enterprise capital (m6) is overvalued in the first equally divided part and undervalued in the fourth equally divided part, for which the reason may be that as enterprises mainly run for profits. The smaller the quantity of capital originating from enterprises is, the less the profiting pressure enterprises will feel, thus slacking off in their innovation, while larger quantity of capital originating from enterprises will force enterprise to acquire more income through increasing innovation efficiency, only so can they ensure profits.

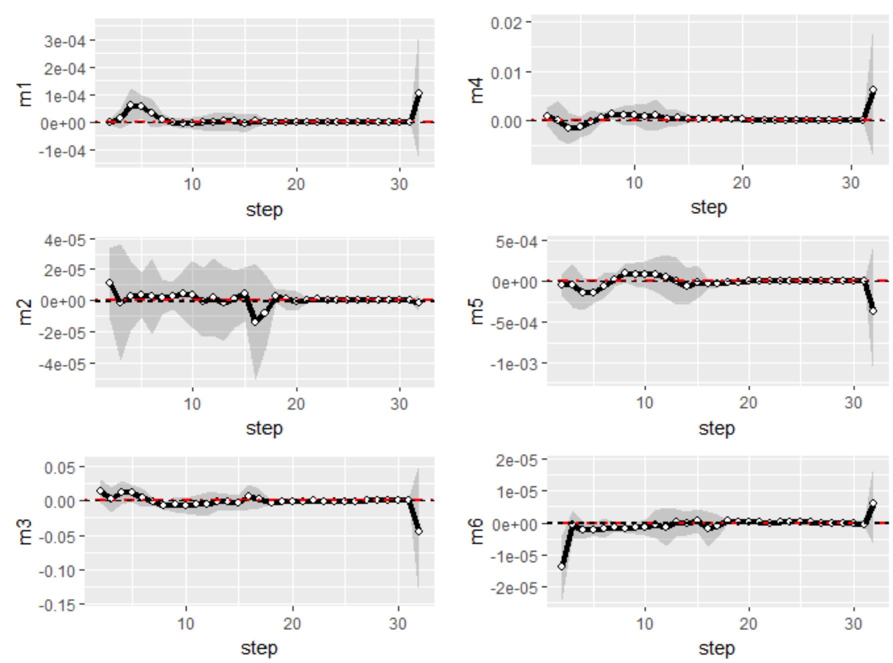

Fig. 2. Factors influencing the innovation efficiency of medium-sized enterprises

4. CONCLUSIONS

The following conclusions are acquired through DEA model analysis and equal part linear regression.

(1) As to DEA efficiency: the number of large-sized industrial enterprises and medium-sized ones belong to DEA efficiency is almost the same, respectively 27 and 26. However, when specifically analysing various subdivided industries, the study finds that large-sized industrial enterprises and medium-sized ones respectively possess certain advantages in different industries.
(2) As to returns to scale, the innovation efficiency of large-sized industrial enterprises is similar to that of medium-sized ones. Half of the industries analysed show constant returns to scale, and nearly 40% are experiencing diminishing returns to scale, leaving only a minority of them featured by increasing returns to scale.
(3) As to input redundancy and output insufficiency, only in the manufacturing industry, the overall input redundancy degree of large-sized industrial enterprises is higher than that of medium-sized ones. While in other industries, the overall input redundancy degree of the both are low and almost the same. As to output insufficiency, although the output insufficiency degree of large-sized industrial enterprises in the number of patent applications within the manufacturing industry is higher than that of medium-sized industrial enterprises, the output efficiency of innovation activities of large-sized industrial enterprises is higher overall.
(4) As to factors influencing innovation efficiency, for large-sized industrial industries, the following factors can improve their innovation efficiency in a more obvious way: tax calculated and deducted with regard to research and development expenses at lower or higher level, medium-level number of well-educated researchers, lower amount of capital support from the government and higher amount of research and development capital originating from enterprises. For medium-sized industrial enterprises, such factors include tax calculated and deducted with regard to research and development expenses at lower or higher level, tax deducted for high-tech enterprises at the lower level, high-level number of researchers with master degree and higher amount of research and development capital originating from enterprises.

Several suggestions are proposed based on the conclusions mentioned above. Regarding enterprises, they should reasonably determine the number of well-educated researchers to be employed according to their respective volumes (large or medium size), quantity and capacity of available resources, thus avoiding personnel redundancy. Besides, according to the results of equal part linear regression, larger amounts of research and development capital originating from enterprises can better stimulate the innovation motivation, and thus attention should also be paid to balancing capital sources to improve the science and technology innovation efficiency of enterprises. Regarding industries, the manufacturing industry should optimise the input structure of research and development expenses, management expense and the expense on the absorption of technologies introduced, and strengthen the attention to patent applications. Finally, in terms of government, according to the results of equal part linear regression, excessively high support from government may make enterprises slack off in innovation so that it is necessary for the government to truly understand the mechanism of efficient innovation of enterprises and formulate reasonable innovation support policies.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Zhao SK, Yu HQ and Kong SL. The innovation efficiency of hi-tech enterprises in Jilin Province based on DEA method. Scientific Research Management. 2013; 34(02):36-43.
2. Xiong C, Mai YY, He XB, Xiao RQ. A study on operational efficiency of hi-tech startups in china based on DEA methods. Journal of Management Science. 2014;27(02):26-37.
3. Hung SW, Wang AP. Entrepreneurs with glamour? DEA performance characterization of high-tech and older-established industries. Economic Modelling. 2012;29(4):1146-1153.

4. Romijn H, Mike A. Innovation, networking and proximity: Lessons from small high technology firms in the UK. Regional Studies. 2002;36(1):81-86.
5. Sun Guofeng, Zhang Chan, Yao Dewen. The measure of China's large and medium-sized Hi-tech enterprises efficiency and decomposition: An empirical analysis based on DEA model. Journal of Audit & Economics. 2016;31(03):111-119.
6. Liu CK, Zhang XW. Evaluation and analysis of R&D efficiency in small and medium-sized high-tech enterprises: Based on the three-stage DEA model. Science & Technology and Economy. 2017; 30(06):41-45.
7. Chen W, Jing R, Zhang HQ, Hou J. The evaluation of large and medium-sized industrial enterprises technological innovation efficiency in Northeast China: Based on the DEA-Malmquist index method. East China Economic Management. 2017;31(02):66-71.
8. Wang H. Study on governance effect of capital structure of listed real estate companies. Science and Technology and Industry. 2011;11(01):49-55.
9. Wong CY, Mohamad ZF, Keng ZX, Azizan SA. Examining the patterns of innovation in low carbon energy science and technology: Publications and patents of Asian emerging economies. Energy Policy. 2014; 73(05):789-802.
10. Vásquez-Urriago AR, Barge-Gil A, Rico AM. Science and Technology Parks and cooperation for innovation: Empirical evidence from Spain. Research Policy. 2016;45(01):137-147.
11. Albahari A, Pérez-Canto S, Barge-Gil A, Modrego A. Technology parks versus science parks: Does the university make the difference. Technological Forecasting and Social Change. 2017;116:13-28.
12. Sun CC. Evaluating and benchmarking productive performances of six industries in Taiwan Hsin Chu Industrial Science Park. Expert Systems with Applications. 2011; 38(03):2195-2205.
13. Pan WT. A newer equal part linear regression model: A case study of the influence of educational input on gross national income. EURASIA Journal of Mathematics Science and Technology Education. 2017;13(8):5765-5773.

Peer-review history:
The peer review history for this paper can be accessed here:
http://www.sciencedomain.org/review-history/26456