Research on Financing Efficiency of New Energy Companies in China Based on Multi-stage Super-DEA Model

GENG Cheng-xuan[1], WANG Qiong[1,2], E Hai-tao[1], LI Meng[1]

[1]College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing, 211106, China, [2]School of Mathematics and Physics, Changzhou University, Changzhou, 213164, China

This work was supported in part by the Chinese National Social Science Fund Project 15BGL056; Key Project of Jiangsu University Philosophy Social Science Research 2015ZDIXM008; The Central Special Cultivating Funds of Basic Business Expenses of Major Scientific Research Projects NP2015302

ABSTRACT

Combing with Tobit regression and SFA model, a multi-stage Super-DEA model can exclude the environmental effects and stochastic effects. It is employed to assess financing efficiencies of 104 new energy listed companies in 2016. The empirical results show that most actual financing efficiencies are not efficient. The scales of these companies are the main constraint on their development. And the special technical level also has an impact on these efficiencies. In addition, the efficiency difference among provinces in China gives another support to environmental influence on the new energy industry. 93.27% of companies are in the stage of increasing returns to scale. Therefore, a new energy company should pay attention to expanding its scale of production and heighten its special technical level as well as improve their financing efficiencies with the help of local government power.

Keywords: New Energy Industry, Financing Efficiency, Multi-stage DEA Model, Tobit Regression, SFA

I. INTRODUCTION

To speed up the cultivation and development of new energy industry is not only a trend of global industrial restructuring, but also a major choice for the Chinese government to promote economic development model transformation and industrial structure upgrading. The capital is the core and artery for the development of new energy industry. In the new normal economy, the financing efficiencies of new energy companies are severely constrained by the real financing ecosystem. How to achieve higher financing efficiency has become an important issue in the limited supply of capital resources. It may provide a more profound theoretical interpretation and more fully empirical evidence for the strategic emerging industries.

This work was supported in part by the Chinese National Social Science Fund Project 15BGL056; Key Project of Jiangsu University Philosophy Social Science Research 2015ZDIXM008; The Central Special Cultivating Funds of Basic Business Expenses of Major Scientific Research Projects NP2015302.

The initial research on financing theory and efficiency theory of foreign scholars emerged in 1950s. Companies' financing efficiencies in western countries are often efficient because of their mature property system and property rights' system. Therefore, there are most literatures focusing on allocation efficiency of financial structure or market, but little literature about financing efficiency. Yilmaz et al. [1] studied the relationship between product market competition and financial structure of listed companies based on a series of static and dynamic data. By theoretical models, Hovakimian, Opler and Timan [2] found that a company should choose debt financing to support its current business and choose equity financing to ensure its need to grow in order to improve its financing efficiency. Based on the sample of Spanish listed companies during 1998-2008, improving financial leverage helps to reduce excessive investment, and improving debt maturity structure helps to raise financing efficiency, thus reduce excessive investment and insufficient capital investment[3].

Since the conception of financing efficiency was firstly proposed by Zeng (1993) [4], many scholars in China have further research on financing efficiency. The concept of financing efficiency is often different to different scholars, but its basic connotation is the ratio of input to output, or the ratio of cost to income. The financing efficiency of enterprises is to create the financing capacity of the enterprises value. Only if compared with other companies and with its past, a company will know its financing efficiency. Long-term debt financing was little influence on small and medium enterprises using the gray correlation analysis method [5]. Cheng et al. [6] researched relative efficiencies of listed companies in strategic emerging industries during

2005-2011 using BCC model and most efficiencies are not efficient. Huang et al. [7] selected Beijing high-tech industry data during 1995-2009, and measured technical efficiencies with SFA and three-stage DEA model. Additionally, Xiong et al. [8] built a Logit model to analyze effective factors of efficiencies obtained by DEA method. It indicated that the macroeconomic situation has a far-reaching impact on promoting the strategic development of new industries. Liu et al. [9] concluded that the quality of state-owned enterprises' development is better than the private enterprises'.

Based on relevant literatures, compared with other methods, the DEA method is relatively objective to determine weights of inputs and outputs [10]. But the study on financing efficiency at present is mainly based on a low-stage DEA model. There are some defects in the low-stage DEA model. For example, two-stage DEA model cannot make full use of the slack variable information. Three-stage DEA model does not take variable truncation in Stochastic Frontier Analysis (SFA) into account, which the parameter estimations obtained are not consistent. Although parameter estimates are consistent in Tobit model, four-stage DEA model cannot adjust the stochastic effect.

Combined with Tobit model and SFA, multi-stage Super-DEA model is proposed to assess financing efficiency of new energy listed companies in China. This model can filter the effect of both external environmental and stochastic factors to obtain pure financing efficiencies operating in the same ecological environment along with the same fortune. The input-oriented Super-DEA model offers initial financing efficiencies without these effects in the second stage. Later, all environmental variables are judged their direction of impact on financing efficiencies in Tobit regression model. In the fourth stage, the estimates in SFA regression are obtained and then employed in the adjustment of inputs. Then repeat the input-oriented Super-DEA model with adjusted inputs and initial outputs to obtain final financing efficiencies. The results show that the importance and necessity of making such adjustments to assess financing performance of companies.

The next section provides more details of the methodology followed by the explanations of data sources, variable selections and empirical analyzing. The final section is a conclusion.

II. METHODOLOGY

Assessing efficiencies will begin with input-oriented Super-DEA model along with BCC-DEA model (variable returns to scale, VRS) which Banker, et al. proposed in 1984 [11]. Then the analysis combined with Tobit regression and SFA model will proceed to consider the effects of environmental factors on efficiencies obtained from the DEA model. The empirical analysis will focus on financing efficiencies. Given different financing channels, choosing an input-oriented DEA model to assessing efficiencies is appropriate. In view of the maximization of profits, companies are asked to produce the same or more with less. Therefore, input-oriented Super–DEA model with VRS is employed in the paper.

A. Stage 1 and Stage 2: Index Selection and Super-DEA Model

We begin with each of n companies with m inputs and q outputs. Ideally, company management has thoroughly control over these inputs which impact all outputs. For the j^{th} decision unit, the corresponding standard input and output data are respectively noted as the following:

$$x_j = (x_{1j}, x_{2j}, ..., x_{mj})^T, y_j = (y_{1j}, y_{2j}, ..., y_{qj})^T \quad j = 1, 2, ..., n \tag{1}$$

By standard notation [12], the linear programming of Input-oriented Super-DEA model in the first stage under consideration is as the following.

$$\begin{aligned} & \min \theta \\ s.t. \quad & \sum_{\substack{j=1 \\ j \neq k}}^{n} \lambda_j x_{ij} \leq \theta x_{ik} \\ & \sum_{\substack{j=1 \\ j \neq k}}^{n} \lambda_j y_{rj} \geq y_{rk} \\ & \sum_{\substack{j=1 \\ j \neq k}}^{n} \lambda_j = 1 \\ & \lambda_j \geq 0 \\ & i = 1, 2, \cdots, m; j = 1, 2, \cdots, n; r = 1, 2, \cdots, q \end{aligned} \tag{2}$$

In model (2), q is financing efficiency of DMU$_k$, and l are weights of inputs (x) or outputs (y) for companies. The number of inputs (x) is m in total, described in more detail in the following section. The model results in assessing the operating performance of each company. Companies are considered as efficient units if $\theta \geq 1$.

The estimates of financing efficiencies obtained in Super-DEA model include three effects: (1) the different allocation of financing resources in management decisions; (2) the different external environment in which companies are operating; (3) stochastic events that impose good or bad fortune to companies. Since Super-DEA model cannot differentiate the initial efficiencies which are due to the internal or external factors, it is unfair for companies with an unfriendly environment to compare with companies with a relatively friendly environment. Modified efficiencies will be equal for those companies with the same managerial competencies, if inputs are adjusted to place companies with additional resources in unfriendly provinces to those in a non-differentiated environment. Therefore, the following stages are required.

B. Stage 3: Tobit Regression

Four-stage DEA model proposed by Fried, et al. [13], accounts for external environmental effects to isolate the inefficiency performance due to the management competency of companies. As the dependent variable, financing efficiencies are truncated on the left by 0. Then, Tobit regression model is employed in this stage, in which dependent variables are truncated. Consequently, Tobit regression model is constructed as follows:

$$\theta_j = \beta_0 + \sum_{k=1}^{K} \beta_k e_{kj} + \varepsilon_j \quad k = 1,2,...,K;\ j = 1,2,...,n \tag{3}$$

In model (3), $\theta_j\,(j = 1,2,...,n)$ is the initial financing efficiency of DMU$_j$, and the independent variable e_{kj} represents the k^{th} environmental variable of DMU$_j$. b$_k\,(k = 0,1,2,...,K)$ is regression coefficients to be estimated. $\varepsilon_j \sim N(0,\sigma^2)(j = 1,2,...,n)$ represents independent residual terms. K is the number of environmental variables.

Tobit regression model is used to identify the direction of environmental impact on initial financing efficiencies. If a regression coefficient $\beta_k\,(k = 1,2,...,K)$ is positive and statistically significant, increasing the corresponding external environmental variable helps to improve the efficiencies. In other words, the changing direction of this environmental factor is the same with financing efficiencies. Therefore, this factor is considered to be detrimental to financing efficiencies. Then it is called a negative environmental variable e_k^-. Otherwise, it is called a positive environmental variable noted by e_k^+.

C. Stage 4: SFA

In this stage, SFA is applied to modify the disadvantages of Super-DEA model which is difficult to deal with external environment and stochastic disturbance factors. Slack variables of initial inputs are selected as dependent variables, and all negative environmental variables as explanatory variables in SFA regression. The specific SFA cost equation is as the following.

$$s_{ij}^- = \sum_{k=1}^{K_1} \beta_k e_{kj}^- + v_{ij} + u_{ij} \quad (i = 1,2,\cdots,m;\ j = 1,2,\cdots,n) \tag{4}$$

In model (4), $v_{ij} \sim N(0,\sigma_v^2)$ represents the stochastic error term beyond the control of DMU$_j$, and $u_{ij} \sim N^+(\mu,\sigma_u^2)$ represents the inefficient item which DMU$_j$ can control but is not yet efficient. v_{ij} and u_{ij} are independent and irrelevant. K_1 is the number of negative environmental variables.

Compared with nonparametric methods, the main advantages of SFA method are to distinguish stochastic factors from technical inefficiencies and test econometrically on the regression model. Essentially, the explained variable is discomposed as three parts, namely cost function, stochastic factors and technical inefficiency. After adjusting initial inputs according to external environmental and stochastic factors as well as deeper information mining, an objective and comprehensive evaluation will be obtained from Super-DEA model.

D. Stage 5 and Stage 6: Inputs Adjustment and DEA Model

Using the maximum fitted value of each input variable and stochastic error term, all initial inputs are adjusted. The formula for adjustment is as the following.

$$x_{ij}^{adj} = x_{ij} + [\max_j\{\hat{s}_{ij}^-\} - \hat{s}_{ij}^-] + [\max_j\{\hat{v}_{ij}\} - \hat{v}_{ij}] \ \ i = 1,2,...,m; j = 1,2,...,n \quad (5)$$

In equation (5), x_{ij}^{adj} is the adjusted i^{th} input of DMU$_j$, and $\hat{s}_{ij}^-$ is the slack fitted value from SFA regression. The random error term v_i is estimated by

$$\hat{E}[v_i \mid v_i + u_i] = s_i - z_i \hat{b} - \hat{E}[u_i \mid v_i + u_i] \quad (6)$$

After the above adjustment, x_{ij}^{adj} can not only punish those DMUs with better performance and higher efficiency due to friendly external environment, but also filter stochastic factors of DMUs. In other words, all DMUs have the same fortune and are in the most severe external environments.

The final stage is once again the application of input-oriented Super-DEA model but with the inputs adjusted by Equation (5) and initial outputs. Due to excluding the effect of external environmental and stochastic factors, final efficiency estimates can reflect pure financing efficiencies of DMUs.

III. DATA AND INDEX SYSTEM

Before you begin to format your paper, first write and save the content as a separate text file. Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any kind of pagination anywhere in the paper. Do not number text heads-the template will do that for you.

Finally, complete content and organizational editing before formatting. Please take note of the following items when proofreading spelling and grammar:

E. Data Sources

This paper selected new energy listed companies as the initial sample from Shanghai and Shenzhen Stock mark in 2016. To keep the consistency of the data sample, the sample followed by the following criteria: (1) excluding ST stocks and delisted stocks, because these companies' financial data are abnormal; (2) excluding the listed companies lack of related data; (3) eliminating the effects of extreme values, by Winsorization at 1% level. Finally we selected 104 listed companies as the final sample. All data are from CSMAR database and China's statistical yearbook.

F. Index System

We consider two kinds of financing channels, including internal financing and external financing. The external financing involves debt financing and equity financing. According to relevant literature, surplus reserve and undistributed profits are chosen as internal financing inputs to measure internal investment intensity, noncurrent liabilities as debt financing input, paid-up capital and capital surplus as equity financing inputs to measure exogenous investment intensity. The financing performance of listed companies includes the market performance and management level. Then gross revenue and net profit are selected as outputs to measure the revenue of a company. The principle of selecting environment variables is that environmental variables have some effects on outputs, but are uncontrolled by companies. Of environmental variables, RMB loans balance of financial institutions at year-end in local region represents to financial supporting on the development of new energy companies, the number of patents in local region over the past three years represents the influence of local innovation environment on the development of new energy companies, and current GDP represents local market demand [14]. These environmental variables reflect the different aspects of external environments in which companies are operating. A summary of above-mentioned variables are presented in Table 1.

IV. EMPIRICAL ANALYSISE

G. A First Stage Descriptive Analysis

The descriptive analysis of all variables is shown in Table 2. Each variable differs greatly among companies. The difference between maximum and minimum of environmental variables is more than 150 times. For example, the maximum of E1 is

698.52, but the minimum of E1 is only 39.10. Therefore, it is necessary to exclude these environmental effects. Super-DEA model requires all values of inputs and outputs should be positive, but actual data may exist negative such as undistributed profits and capital surplus. Therefore, all data are processed to be positive by adding some constants [15].

According to the DEA index selection principle, all input variables should have positive effects on the company's expected outputs. In other words, outputs must not be reduced by increasing inputs. Person correlations are tested and the specific results are presented in Table 3.

From Table 3, all correlation coefficients between inputs and outputs are positive, and most of them are significant at the 1% significant level by two-tailed test. It indicates that there are indeed significant positive correlations between inputs and outputs. Besides, the number of DMUs is 104, far more than the number of all input and output variables. It conforms to the principle of index selection. Consequently, these variables are appropriate for assessing financing efficiencies by Super-DEA model.

H. Second Stage Super-DEA

Based on input-oriented Super-DEA model, we can obtain financing efficiencies of companies by MATLAB Software. The results are shown in Table 4 and Figure 1.

Table 1: Index system with input, output and environmental variables

First order	Second order	Third order	Notation
Input variable	Debt financing	Noncurrent liabilities	Input 1
	Internal financing	Surplus reserve	Input 2
		Undistributed profits	Input 3
	Equity financing	Paid-up capital	Input 4
		Capital Surplus	Input 5
Output variable	Revenue	Gross Revenue	Output 1
		Net profit	Output 2
Environmental variable	Financial environment	Local RMB loans balance of financial institutions at Year-end	E1
	Technological innovation	Local cumulative number of patents granted in the past three years	E2
	Market demand	Current gross domestic product	E3

Table 2: Index system with input, output and environmental variables

Variable	Mean	Median	Maximum	Minimum	Standard deviation
Input 1	8034.5	370.8	164956.4	0.0	25649.0
Input 2	808.9	88.1	18284.1	0.0	2705.1
Input 3	1951.2	544.1	37606.5	–7570.2	5710.7
Input 4	1946.5	723.6	19650.4	119.5	3514.9
Input 5	2467.9	1169.1	28549.2	69.3	3984.9
Output 1	9085.3	2648.9	210921.3	130.1	25787.9
Output 2	896.7	136.1	17549.7	–4452.3	2666.7
*E*1	442.89	443.58	698.52	39.10	207.05
*E*2	359.10	231.36	689.97	4.50	256.98
*E*3	410.29	349.39	677.92	27.52	207.03

Table 3: Correlation between the input and output variables

Variable	Input 1	Input 2	Input 3	Input 4	Input 5
Output 1	0.730***	0.630***	0.527***	0.757***	0.600***
	0.000	0.000	0.000	0.000	0.000
Output 2	0.850***	0.580***	0.943***	0.783***	0.753***
	0.000	0.000	0.000	0.000	0.000

***p<0.01

Table 4: Financing efficiencies with unadjusted inputs

Efficiency	Mean	Median	Maximum	Minimum	Standard
CRS	1.042	0.962	2.740	0.358	0.352
VRS	1.227	0.999	4.267	0.710	0.626
SC	0.894	0.960	1.065	0.279	0.154
Efficiency	**Efficient,#**	**Efficient,%**	**Constant**	**Decreasing**	**Increasing**
CRS	38	36.54			
VRS	51	49.04			
SC	4	3.85	3.85%	71.15%	25.00%

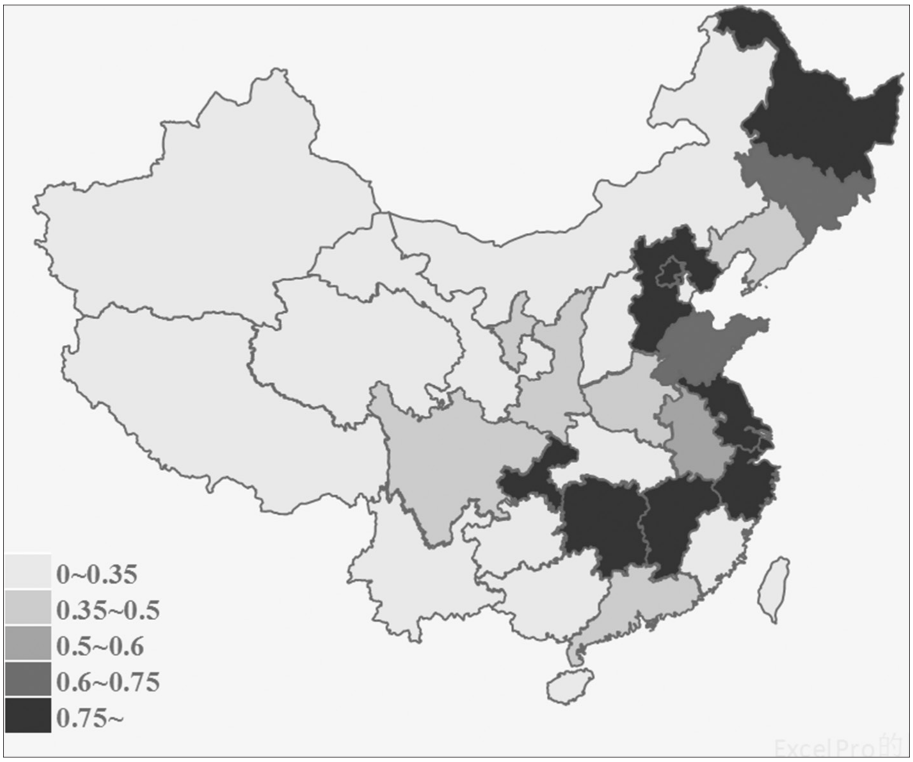

Figure 1: Initial Financing Efficiencies

From Table 4, the means of overall financing efficiencies (CRS), pure technical efficiencies (VRS), and scale efficiencies (SC) of 104 new energy listed companies are 0.821, 0.867 and 0.947, respectively. It indicates that if operating effectively, each company may maintain these outputs with fewer inputs. Specifically, most companies had capital redundancy and made no full use of funds after financing. There is still room to enhance overall financing efficiencies of new energy companies. Moreover, there is a stark difference among financing efficiencies. For example, the minimum financing efficiency is surprisingly low at 0.2358 under CRS. It indicates that about 76.42% capital financing is inefficient. 25% companies are in the stage of increasing scale return to scale. Hence, these companies can increase their inputs to obtain their more outputs in the equal proportion. Only 36.54% companies are efficient. In summary, financing efficiencies of new energy industry in China remain to be improved in the future.

I. THIRD STAGE TOBIT

The environmental effects on financing efficiencies can be determined by Tobit regression model. Specific results in Tobit model are shown in Table 5. The coefficients of environmental variables $E1$ and $E3$ are positive and highly significant, indicating that the greater the variables $E1$ and $E3$, the greater the financing efficiencies of companies. Therefore, they are negative environmental variables. But the coefficient of environmental variable $E2$ is negative and highly significant. The changing direction of this environmental variable $E2$ is different from financing efficiencies. According to the principle of the same direction, this environmental variable $E2$ is a positive environmental variable.

J. Fourth Stage SFA and Fifth Stage Adjustments

Because input-oriented Super-DEA model is employed in this paper, we need to consider just the adjustment of negative variables on input slacks. SFA regression with variables *E*1 and *E*3 is applied to all input slacks. In SFA regression, the estimates of inefficiency components obey the law of a half-normal distribution. The results of SFA regression is shown in Table 6. For the estimates of five slack variables, managerial inefficiency is significant in determining input redundancies. Actually, the gamma estimates of all slacks are very close to 1, which means these input slacks are mainly due to management. These results also show that two environmental variables affect significantly input slacks. The coefficients for variable *E*3 are consistently negative in input4 and input5 slacks, suggesting that the financing efficiencies are in line with a favorable or friendly operating environment. The better this environmental condition, the less excess the input4 and input5. In the remaining slacks, the effects of *E*3 are positive and significant. All coefficients of environmental variable *E*1 are positive. The likelihood ratios are statistically significant which support the frontier specification.

K. Final Stage Super-DEA

According to the results of SFA regression, the maximums of input slacks obtained from the SFA regression are due to the environmental effects, while the means due to statistical noise. The adjusted inputs of the final stage are computed by Equation (5). The final efficiencies are recalculated with adjusted inputs and initial outputs to eliminate external environmental effects. In addition, there is the same fortune at work as indicated by statistical noise. The results are given in Table 7.

Compared to initial financing efficiencies, final financing efficiencies are changed with the adjustments for external environmental factors and good or bad fortune. As far as CRS and VRS are concerned, the means decrease by 21.21% or 19.23% compared to initial efficiencies. The mean efficiency of VRS decreases from 1.227 to 0.991. The median VRS efficiency with the adjusted inputs is 0.960, a decrease of 3.90% points. There is a great change in the minimum of company efficiencies under CRS (from 0.358 to 0.641) and VRS (from 0.710 to 0.803). Although these changes of financing efficiencies are not dramatic, it must be noted that the number of efficient companies under CRS decrease by 73.68% (from 38 to 10). The change of financing efficiencies supports that financing efficiencies are greatly affected by market demand and financial environment. For returns to scale (RTS), about 71.15% of companies are in the stage of decreasing returns to scale in the second stage, but nearly 93.27% of companies are in the stage of increasing returns to scale after adjusting inputs. It indicates that 93.27% of companies can improve their financing efficiencies by increasing their inputs.

Table 5: Tobit regression of financing efficiencies

Variable	Coefficient	Standard error	z-statistic	Prob.
*E*1	0.0032***	0.0480	6.1495	0.0000
*E*2	−0.0019***	0.0388	−4.5993	0.0000
*E*3	0.0005**	0.0447	2.2309	0.0223

**p < 0.05 ***p < 0.01

Table 6: SFA regression of input slacks for environmental variables

	Slack 1	Slack 2	Slack 3	Slack4	Slack5
Constant	−24533.93***	−2562.35***	−1019.44***	−1583.35***	−747.46***
	(1.000)	(1.000)	(1.000)	(1.000)	(0.999)
*E*1	33.56***	0.14	0.97***	3.60***	1.53***
	(3.718)	(0.855)	(0.729)	(0.359)	(0.066)
*E*3	1.52*	3.92***	0.51***	−1.67***	−0.54**
	(3.524)	(0.742)	(0.712)	(0.249)	(0.302)
Sigma2	0.11E+10	0.12E+8	0.26E+7 ***	0.53E+7***	0.39E+7***
	(0.983)	(1.000)	(1.000)	(1.000)	(1.000)
Gamma	0.999***	0.999***	0.999***	0.999***	0.999***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log likelihood	−1140.86***	−904.09***	−823.66***	−861.53***	−843.27***
$\max_j\{\hat{s}_{ij}^-\}$	61.08	192.90	3.87	1.44	5.77
$\max_j\{\hat{v}_{ij}\}$	2.65	3.74	0.65	0.23	1.19

*p < 0.1, **p < 0.05 ***p < 0.01 and the values in brackets are standard-errors of estimates

The financing efficiency ranking can provide a new insight into the adjustment effects with different operating environments. Using the CRS estimates, above-mentioned adjustment resulted in 49 companies improving their ranking and 55 companies slipping down. Obviously, it is inappropriate to ascribe all changes of ranking that are caused by adjusting local financial environment. Moreover, there are other environmental factors and good or bad fortune at work. Unfortunately, marginal effect analysis is impractical for all possible environmental combination involved. From financial environmental perspective, the comparison between two financing efficiency rankings was carried out.

To uncover how the adjustment to initial inputs can result in the efficiency ranking change for financial environmental effect, this environmental variable E1 is divided to three classes. The specific results are shown with a decomposition of changes in Table 8. 26 of 104 companies in friendly financial environments improved their rankings by adjusting initial inputs. Ranking improvements occurred for 5 of 26 companies in unfriendly financial environments. But there are 27 of 52 companies in the second group of financial environment. Another comparison is presented in the fifth column of Table 8. The means of efficiency ranking change in three groups of financial environmental variable $E1$ are 16.46, 0.06 and -16.58. In summary, the central companies with the middle range of E1 will experience a great progress if the financial environment changes to be friendly. In contrast, the third group will witness less progress.

V. CONCLUSIONS

New energy companies are facing operating environmental changes. A focus on financing environments helps to evaluate real financing performances. To do this, financing efficiencies from Super-DEA model are compared with those from the modified model with the adjustment for both environmental and stochastic effects in this paper. The financing efficiencies in the final stage rely on Tobit and SFA regression which parametrically determined the adjustments to inputs. Therefore, the modified efficiencies are based on the same fortune and external environmental factors that the company decision-makers cannot control. The latter are determined by financial and market environment and measured as the differences in the local RMB loans balance of financial institutions as well as gross domestic product.

The results indicate that the mean increment of efficiencies is -0.221, from 1.042 in Super-DEA model to 0.821 in the multi-stage DEA model. Although current efficiency changes are not dramatic, the weak difference for company efficiencies does not reduce the necessity and importance of the adjustment process. A significant difference resulting from the adjustment are found to be the decrease in the number of efficient companies from 38 to 10, or a nearly 73.68% decrease. Thus, the combined evidence supports the negtive shift of efficiency distribution as well as the change of company efficiency ranking. Moreover, the latter would be more important if any company performance takes efficiency differences in financial ecological environment in account.

From the above discussions, the financing efficiencies of new energy industry in China still remain to be improved. On the one hand, most company should focus on expanding their scales of production and encourage technological innovation. They

Table 7: Financial efficiencies with adjusted inputs

Efficiency	Mean	Median	Maximum	Minimum	Standard
CRS	0.821	0.769	1.670	0.641	0.153
VRS	0.991	0.960	3.202	0.803	0.246
SC	0.837	0.805	1.508	0.772	0.103
Efficiency	**Efficient,#**	**Efficient,%**	**Constant**	**Decreasing**	**Increasing**
CRS	10	9.62			
VRS	11	10.58			
SC	2	1.92	0	6.73%	93.27%

Table 8: Efficiency ranking changes

E1	N	Δ>0	Δ<0	meanΔ
$E1\geq250.32$	26	17	9	16.46
$51.67\leq E1<250.32$	52	27	25	0.06
$E1<51.67$	26	5	21	−16.58
Total	104	49	55	0

should gradually optimize their governance structures and develop the ability of financing technological progress. On the other hand, we should maintain and strengthen financial support of the financial system, as well as resort to local governmental power to improve financing efficiencies.

ACKNOWLEDGMENT

This research is supported by National Social Science Foundation of China (15BGL056), Key Projects from Philosophy and Social Science Fund of Universities in Jiangsu Province (2015ZDIXM008), and Fundamental Research Funds for Central Universities (NP2015302). Moreover, we are grateful for the anonymous referees for their careful evaluation and critical comments, which greatly improved the quality of this paper.

REFERENCES

[1] Yilmaz Guney, Ling Li, Richard Fairchild. "The Relationship between Product Market Competition and Capital Structure in Chinese Listed Firms". *International Review of Financial Analysis*. Vol. 20, pp. 41-51, 2011.
[2] Hovakimian, Opler, Timan. "The Financing and Technology Decisions of SMEs: Finance as a Determinant of Investment". *Work Paper*, 2013.
[3] Fuensanta Cutillas Gomariz, Juan Pedro Sánchez Ballesta. "Financial Reporting Quality, Debt maturity and Investment Efficiency". *Journal of Banking and Finance*, vol.3, pp. 494-506,2014.
[4] Zeng K.L. "What about Direct Financing and Indirect Financing". *Journal of Financial Research*, vol.10, pp.7-11,1993.
[5] Liu, L.C., Feng, G.F., Zhang, D.H., Mao, H.X. "Efficiency Evaluation on Equity Finance of Listed Companies on Basis of DEA". *Systems Engineering*, vol.22, pp.54-59,2004.
[6] Cheng G.S., Zhang Y., Rui M.J. "On the Relative Efficiency between State-Owned and Private Enterprises in the Development of Strategic Emerging Industries: An Empirical Analysis Based on the Data of Listed Companies from 2005 to 2011". *Contemporary Finance and Economics*, vol.10, pp. 96-105,2013.
[7] Huang, L. C., Zhang, X. M., Wu, F. F., et al. "Empirical Study on the Technical Efficiency of Beijing High-tech Industry Based on Three-stage DEA Model". *Technology Management for Emerging Technologies Vancouver*, Canada, pp. 3352-3357,2012.
[8] Xiong Z.D., Zhan B., Lin X. "The Efficiency of Financial Support about Strategic Emerging Industry Based on DEA and Logit Model". *Systems Engineering*, vol.29, pp. 35-41, 2011.
[9] Liu Y, Peng M. "A Comparative Study on Technical Efficiency of New Energy Listed Companies of Different Ownership Types in China—An Empirical Study Based on DEA-Malmquist". *Journal of Industrial Technological Economics*, vol.3, pp. 38-43,2015.
[10] Ye S.Y., Wang H. "Research on Decision Making Units' Homogeneity of Multiply –stage DEA". *Statistics &Information Forum*, vol.27(2), pp.15-21, 2012.
[11] Banker R.D., Cooper W.W. "Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis". *Management Science*, vol.30(9), pp. 1078-1092, 1984.
[12] Cook, W.D., Tone, K., Zhu, J. "Data envelopment analysis: prior to choosing a model". *Omega*, vol.44(2), pp. 1-4, 2014.
[13] Fried H.O., Yaisawarng S. "Accounting for Environmental Effects and Statistical Noise in Data Envelopment Analysis". *Journal of Productivity Analysis*, vol.17, pp. 157-174,2002.
[14] Zeng S., Hu M., Su B. "Research on Investment Efficiency and Policy Recommendations for the Culture Industry of China Based on a Three-stage Dea". *Sustainability*, vol.8(4), pp. 1-15, 2016.
[15] Ma Z.X., Tang H.W. "On the Invariant Properties of DEA Method under the Data Transformation". *Journal of Systems Engineering*, vol.14(2), pp. 129-134, 1999.