Chongqing High-tech Industry Performance Evaluation

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Abstract. The technology innovation performance of high tech industry in Chongqing 1997-2013 is studied by using the super efficiency DEA and ARDL model. Firstly, the relative effective and invalid years of DEA are analyzed from the technology and scale of input output, and the projection value of the invalid years is improved. Secondly, the introduction of lag concept, the ARDL model to analyze the regional investment the influence degree of the factors on innovation output. Finally, this paper puts forward the pertinence suggestion of improving the technological innovation performance of high tech industry in Chongqing.

Introduction

High-tech industry is a focus of theorists. Many scholars have harvested some original, creative research findings from this field. Wang Changchun(2011) used panel data to explore the innovation performance of high-tech industries in China's 26 provinces (and municipalities) by the stochastic frontier method[1]. Liu Xin(2013) employed the factor analysis method to carry out a comprehensive evaluation, which vertically and horizontally evaluated the innovation performance of high-tech industries in multiple regions and, on this basis thereon, further analyzed factors affecting regional innovation[2]. QianWenyu(2014) used the 2009-2011 data of China's high-tech industry in technological innovation to study the efficiency of innovation, analyze the problem of excessive investment, and propose recommendations for improvement[3].

Nowadays, few scholars would apply super-efficiency DEA approach and ARDL model to analyze DEA inefficiency years and study the impact of input elements on innovation output via the autoregressive distributed lag (ARDL) model. This paper studied the technological innovation of Chongqing's high-tech industry on the basis of super-efficiency DEA approach and ARDL model; employed GDP deflator to eliminate price fluctuations and principal component analysis to reduce the dimension for data processing; introduced lag and ridge regression into the model; and gave some suggestions on how to improve.

DEA Empirical Analysis of Innovation Performance: Based on Chongqing Data

Evaluation Indicator System and Data. Based on the following inputs and outputs, the innovation performance of Chongqing's high-tech industry was evaluated from the perspective of multiple inputs/outputs, that is, using the DEA approach to select multiple inputs and multiple outputs to evaluate their performance. In this study, input and output indicators were preliminarily selected in strict line with the principle of scientificity, effectiveness, and feasibility. Input indicators involved

manpower input, financial input, and material input, and output indicators were comprised of intermediate outputs and final outputs, as shown in Table 1 below:

Table 1: Preliminary Input and Output Indicators for Performance Evaluation

Input Indicators			Output Indicators		
Type	Name	Unit	Type	Name	Unit
Manpower Input	No. of employees on average		Intermediate Outputs	No. of patent application cases	
	Researchers full-time equivalent	Persons per annum		No. of effective patents	
Financial Input	Internal expenditure on R&D	In CNY 10,000	Final Outputs	Revenue from main operations	In CNY 100m
	Expenditure on new product development	In CNY 10,000		Revenue from sales of new products	In CNY 10,000
Material Input	No. of businesses				
	Investment in fixed assets	In CNY 10,000			

After the influence of price fluctuation was eliminated with deflator, the data of input and output indicators to be selected were calculated for Spearman's rank correlation coefficient therebetween with SPSS 19.0 After the application of the Spearman's rank correlation coefficient as benchmark to screen the input and output indicators to be selected, finally the researchers full-time equivalent, internal expenditure on R&D, and investment in fixed assets were screened out as the input indicators and the number of efficient patents and the revenue from sales of main products were determined as output indicators (as shown in Table 2).

Table 2: Input and Output Indicators for Performance Evaluation

Input Indicators	Unit	Output Indicators	Unit
Researchers full-time equivalent	Persons per annum	Revenue from sales of new products	In CNY 10,000
Internal expenditure on R&D	In CNY 10,000		
Investment in fixed assets	In CNY 100m	No. of effective patents	

Empirical Results & Analysis.By applying the super-efficiency DEA model to calculate the super-efficiency scores from the weighted input-output data via the *Super-CCR-I* model in software DEA-SOLVER Pro5, results are then obtained in Table 3.

Table 3:1997-2013 DEA Super-efficiency ScoresRegardingTechnological Innovation

DMU	Overall efficiency	Pure technical efficiency	Scale efficiency	Scale changes in yield	Super Efficiency	Ranking
1997	0.665	1.000	0.665	irs	0.665	15
1998	1.000	1.000	1.000	—	1.419	4
1999	0.514	0.753	0.683	irs	0.514	16
2000	0.731	1.000	0.731	irs	0.731	12
2001	1.000	1.000	1.000	—	1.170	6
2002	1.000	1.000	1.000	—	1.173	5
2003	0.701	0.983	0.713	irs	0.701	13
2004	0.766	1.000	0.766	irs	0.766	10
2005	0.819	0.902	0.908	irs	0.819	9
2006	0.683	0.763	0.895	irs	0.683	14
2007	0.447	0.661	0.677	irs	0.447	17
2008	0.905	0.917	0.987	drs	0.905	8
2009	1.000	1.000	1.000	—	1.820	1
2010	0.757	0.806	0.939	irs	0.757	11
2011	1.000	1.000	1.000	—	1.817	2
2012	1.000	1.000	1.000	—	1.013	7
2013	1.000	1.000	1.000	—	1.428	3

NOTE: *irs* stands for increasing return to scale, *drs* for decreasing return to sale, and — for constant return to scale.

The projected value can directly reflect the current demand of a DMU for resource input and the maximum output that might be possibly obtained. It can, on the one hand, direct the DMU to optimize its allocation of resources and, on the other hand, point out the potential of the DMU for future development. Its main function is to facilitate decision-making and inspire the production of recommendations. It is known that among the 17 years from 1997 to 2013, 7 years accomplished DEA comprehensive efficiency and 10 years were evaluated as DEA inefficient in terms of Chongqing's technical output. For decision-making units with DEA inefficiency, CCR-I model (i.e. the input-oriented constant return to scale model) was used in software DEA-SOLVER Pro5, which tried to decrease its input value to improve its relative efficiency and find the cause behind DEA inefficiency. Specific calculation results are shown in Table 4 and Table 5.

Table 4: Improvement to Input Indicators for 10 Years Having High-tech Industry Non-DEA Efficiency

DMU	Researchers full-time equivalent		Internal R&D expenditure		Investment in fixed assets	
	Improved value	Projected value	Improved value	Projected value	Improved value	Projected value
1997	-802	647	-970.32	1926.68	-0.97	1.93
1999	-1005	1014	-3866.38	4092.96	-1.61	1.71
2000	-371	1008	-3706.41	4260.26	-0.86	2.35
2003	-456	1066	-9095.49	9907.44	-2.37	5.55
2004	-366	1199	-6033.86	11354.65	-2.72	8.89
2005	-378	1716	-4300.52	16831.96	-4.37	19.83
2006	-785	1688	-6258.84	13456.86	-10.80	23.22
2007	-1638	1325	-14760.44	11936.58	-28.40	22.97
2008	-342	3272	-2549.38	24353.90	-3.60	34.43
2010	-972	3028	-10489.13	32681.65	-54.15	76.60

Table 5: Improvement to Output Indicators for 10 Years Having High-tech Industry Non-DEA Efficiency

DMU	Revenue from sales of new products		No. of effective patents	
	Improved value	Projected value	Improved value	Projected value
1997	0	50127.00	6	11
1999	0	75318.52	5	10
2000	0	84844.96	0	15
2003	0	172540.93	13	27
2004	0	233308.28	11	53
2005	0	439126.65	96	134
2006	0	458406.51	20	93
2007	0	433459.37	0	103
2008	0	734483.67	30	152
2010	0	984305.40	0	320

It is clear from the analysis that among the 10 years with DEA relative inefficiency, efficiency scores of inputs into, and outputs from, Chongqing's high-tech industry were low and were more or less characterized by the problem of input redundancy or output deficiency. Take Year 2008 which had decreasing return to scale for an example. In 2008, the DEA efficiency was 0.905. Under the category of input indicators, the researchers full-time equivalent had an excess of 342 persons per annum, with the projected value at 3272 persons per annum; the internal expenditure on R&D had an excess of CNY 25,493,800, with the projected value at CNY 243,539,000; and the investment in fixed assets had an excess of CNY 350 million, with the projected value at CNY 3,443 million. Under the category of output indicators, the revenue from sales of new products actually had an output the same with the projected value and the number of effective patents saw a gap of 30, with the projected value at 152. This means that in order to achieve DEA efficiency, the researchers' full-time equivalent must be down by 342 persons per annum, the internal expenditure on R&D down by CNY 25,493,800, and the investment in fixed assets down by CNY 360 million.

ARDL-based Analysis of the Impact of Input Elements

Variable Selection & Dimensionality Reduction. In order to further the analysis of the impact of input indicators on Chongqing's high-tech industry innovation performance, preliminary indicators listed in Table 1 were used. As there were a excessive number of input and output indicators, they should be subject to dimensionality reduction before an empirical test should be conducted via the econometric model. Principal Component Analysis is an overall statistical analysis method which reduces a number of indicators into a few composite indicators for analysis. These few composite indicators can reflect most information of original indicators and be represented as linear combination thereof.

Manpower Input: The principal component score in terms of the average number of employees and the researchers full-time equivalent; **Financial Input:** The principal component score in terms of the internal expenditure on R&D and the expenditure on new product development; **Material Input:** The principle component score in terms of the number of businesses and the investment in fixed assets. **Innovation Output:** The principal component score in terms of the number of patent application cases, the number of effective patents, the revenue from main operations, and the revenue from sales of new products.

Table 6: Independent Variables and Dependent Variables in ARDL Model

Independent variable	Symbol	dependent variable	Symbol
Manpower Input	X ₁	Innovation Output	Y
Financial Input	X ₂		
Material Input	X ₃		

General Model Selection. Following ADF stationarity test, sequences Y, X1, X2 and X3 were thereby obtained, which were stationary sequences of 2nd order; meanwhile, there existed four co-integration relationships between original sequences, of which one co-integration equation implied the existence of positive relationship between output and input in the long run. In the selection of the optimal number of lags, AIC criterion was followed as a basis; so the optimal number of lags selected thereby was 2. Thus, the general model of ARDL is as follows:

$$Y_t = b_0 + \sum_{i=1}^2 b_i Y_{t-i} + \sum_{i=0}^2 \beta_{1i} X_{1(t-i)} + \sum_{i=0}^2 \beta_{2i} X_{2(t-i)} + \sum_{i=0}^2 \beta_{3i} X_{3(t-i)} + \mu_t \quad (4)$$

Optimal Model Selection. After ARDL model with 2 lags was chosen as general model, equation(4) became to have 11 independent variables and 1 dependent variables as shown in Table 7.

Table 7: Right-side Variables of ARDL General Model with 2 Lags

X ₁	X ₂	X ₃	Y
dX ₁	dX ₂	dX ₃	dY
ddX ₁	ddX ₂	ddX ₃	ddY

NOTE: dX₁ represents the data of X₁ with 1 lag and ddX₁ represents the data of reX₁ with 2 lags; This rule applies to others in a similar manner.

In the multiple regression, methods of variable selection mainly include the forward selection, backward elimination, and stepwise regression[7]. Taking into account the full impact of dependent variables on innovation output, this paper chose the backward elimination method to select variables. The advantage of backward elimination is that as long as an independent variable is eliminated, this variable won't be in the model any more. By applying SPSS19.0, the following 7 models were obtained. As per the progression criterion that the probability of F-to-remove be >=0.100, the output results from the software can be reorganized as follows in Table 8.

Table 8: Backward Regression Results

Model	Variable	R ²	RectifiedR ²	F Value	P value
1	ddx1, ddx2, ddx3, dx1, dx2, dx3, dy, x1, x2, x3	0.994	0.980	69.801	0.000
2	ddx2, ddx3, dx1, dx2, dx3, dy, x1, x2, x3	0.994	0.984	95.989	0.000
3	ddx2, ddx3, dx1, dx2, dx3, dy, x1, x3	0.994	0.986	128.104	0.000
4	ddx2, ddx3, dx1, dx3, dy, x1, x3	0.994	0.988	159.256	0.000
5	ddx2, dx1, dx3, dy, x1, x3	0.994	0.989	206.391	0.000
6	ddx2, dx1, dx3, dy, x3	0.992	0.988	235.447	0.000
7	ddx2, dx1, dy, x3	0.991	0.988	286.595	0.000

From 7 models listed in Table 8, it is clear that each model shows fairly good R2 and F, indicating a good fit of the model. For the selection of the optimal model, Model 7 was chosen by the backward elimination method for subsequent study based on the following considerations: the goodness of fit of Model 7 was only 0.3 percent less than Model 1 but the number of independent variables was reduced to 4, and moreover each independent variable had a significant partial

regression coefficient. Thus, Model 7, which is represented as follows, was chosen for subsequent study:

$$\begin{aligned} \hat{Y}_t &= 0.711 + 0.577Y_{t-1} + 1.070X_{1(t-1)} + 1.169X_{2(t-2)} - 0.869X_{3t} \\ se &= (0.080) \quad (0.179) \quad (0.177) \quad (0.174) \quad (0.192) \\ t &= (8.887) \quad (3.227) \quad (6.054) \quad (6.731) \quad (-4.540) \\ p &= (0.000) \quad (0.009) \quad (0.000) \quad (0.000) \quad (0.001) \\ R^2 &= 0.991; \quad F = 286.595, \quad P_F = 0.000 \end{aligned} \quad (5)$$

As can be seen from equation (5), both the innovation output and manpower input of the first year had a positive impact on the innovation output of the second year; the financial input of the first year had a positive impact on the innovation output of the third year; and the material input of the current year had a negative impact on the innovation output of the same year, which, however, isn't in line with the common sense. Because Model 7 is not only an autoregressive distributed lag model but also a multiple linear regression model, there is a need to test the stochastic error of the model for heteroscedasticity and sequence autocorrelation. In addition, also because the impact of material input of the current year on the innovation output of the same year was negative as observed from the regression, it can be inferred that there exists a serious problem of multi-collinearity between independent variables. So, the next step is to test if the stochastic error has any heteroscedasticity or sequence autocorrelation and then measure the severity of each variable's multicollinearity.

Regression Test. The probability corresponding to the statistics is 0.8378. If the null hypothesis is accepted at the 5% significance level, it can be considered that the stochastic error of Model 7 has no heteroscedasticity. The probability corresponding to the statistics is 0.0708. If the null hypothesis is accepted at the 5% significance level, it can be considered that the stochastic error of Model 7 has no sequence autocorrelation. From Table 9, it is known that the VIF of X2 (t-2) in equation (5) of Model 7 is close to 10 and the VIF of the other three variables are greater than 10. So there exists a strong multicollinearity between independent variables of Model 7.

Table 9: Measurement of Multicollinearity

Model		Collinearity Statistics	
		Tolerance	VIF
7	(Constant)		
	dy	0.046	21.593
	dx1	0.046	21.957
	ddx2	0.101	9.942
	x3	0.023	42.956

Due to the presence of a strong multicollinearity, the material input generated a negative impact on innovation output in Model 7, which departs from common economic sense. The following is an improvement of the multicollinearity problem existing between independent variables of Model 7.

Conclusions

Years having technical inefficiency but attaining increasing scale were 1999, 2003, 2005, 2006, 2007, and 2010, where due to great attention to technological innovation, hard efforts were made to combine the self-dependent innovation with the existing innovations that had been brought in, absorbed and recreated to expand the industrial scale and promote the steady development of the industry. The year having both technical inefficiency and decreasing scale was 2008, a year

coinciding with the eruption of the global financial crisis, and inevitably the innovation performance of Chongqing's high-tech industry was adversely impacted.

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