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Evaluation of Green Industry Innovation Efficiency Based on Three-Stage DEA Model: A Case Study of Chinese Information Technology Industry

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Abstract: The information technology industry as a new engine driving China's economy has made more and more contributions to Chinese sustainable development. At present, it has overtaken real estate as the new cradle of Chinese billionaires. The information technology industry not only has its own characteristics of high economic, social benefits, and small impact on the ecological environment, but also can enable the green development of the economy and society. So it is the core industry to support the realization of the "double carbon" goal. This paper evaluated the innovation efficiency of 80 enterprises in the software and information technology service from 2017 to 2018 by constructing a three-stage DEA model. It puts forward countermeasures, which points out the direction for the development of environmental protection and green low-carbon industry. Empirical results show that environmental variables have different effects on innovation efficiency. After excluding the influence of environmental and random factors, the increase in innovation efficiency, while generally significant, is not high. Low innovation efficiency is caused by both pure technical efficiency and scale efficiency, especially pure technical efficiency. Enterprises' adjusted scale returns are mostly increasing; the innovation investment scale is not optimal. Regional differences of enterprise innovation exist; the East and Midwest have obvious polarization both in quantity and quality. These results quantify the effect of the factors affecting enterprise innovation efficiency and put forward policies and suggestions for promoting the development of China's information technology industry accordingly.

Keywords: information technology industry; enterprise innovation; three-stage DEA model

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1. Introduction

In recent years, the rapid development of the world economy has been accompanied by a faster growth of energy consumption. The capacity of resources and environment to contain energy consumption and pollutant emissions required for economic development has been increasingly reduced. Energy constraints have gradually become one of the main factors hindering economic growth. As a knowledge intensive industry, the information industry provides services for technical problems or demands arising from the transmission, provision, and reception of information. It does not generate a large amount of energy consumption and pollutant emissions in its service process. It is inherently green and environmentally friendly, and it can also create huge profits. It has great prospects for development. The development of a high-end technology service industry will further drive the low-carbon and green development of other industries.

About the introductions of industry development and growth status, Schneider and Veugelers (2010) pointed out the source of business survival lied in innovation [1].

Chen (2013) pointed out that the information technology industry in China has some problems, such as “not big”, “not strong”, and “not satisfied” [2]. Han and Li (2017) measured the development level of information industry in 31 provinces and analyzed its spatial and temporal evolution through Kernel density estimation and GIS platform. They found that the Chinese information technology industry improved steadily [3]. Ober, J. pointed (2022) out that open innovation (OI) is among the key strategic resources of enterprises, especially in high-tech sectors such as the ICT industry [4].

In terms of influencing factors for innovation, Müller (2009) [5], Nganga (2011) [6], and Amarjit (2012) [7] deemed that factors such as enterprise size, infrastructure, overall efficiency, R&D investment intensity, and other aspects had significant impacts on corporate growth of small and medium enterprises. Furman (2000) found that companies with strong profitability were more likely to attract government input [8]. Chen and Yang (2016) [9] and Wang and Yu (2019) [10] studied the impact of government subsidies and other stimulus policies on the enterprise innovation of strategic emerging industries, manufacturing industries, electronic information industries, etc. Wu and Liu (2014) studied the impact mechanisms of different subsidy distribution methods on strategic emerging industries innovation which recommended using ratio research and development (R&D) subsidies instead of fixed R&D subsidies [11]. Lu (2017) reviewed the contradictory opinions between R&D investment and corporate performance. Through empirical analysis they found that R&D investment was significantly related to corporate performance, but lag effects existed while R&D personnel input achieved positive promotion effects in the current period [12]. Girod et al. (2017) found the impact of product market regulation on innovation investment was positive, showing a trend of weakness first and then strength [13].Chen analyzed 220 companies listed in the new third board market in 2016, and found that there was a significant positive correlation between the proportion of executives with senior working experience and company growth, while the average age was opposite [14]. R. Osorno and N. Medrano (2020) pointed out the challenges that open innovation platform design encounters are as follows: intellectual property management; costs and benefits to keep the stakeholders’ interest; information structure; governance; quality assurance; and finally associated risks [15]. M, I, and T (2020) pointed out that both internal knowledge at the backers’ level and at the OIPs’ level have a positive impact on the outcomes of the initiatives [16]. In addition, there was no significant correlation between the shareholding ratio of senior executives, the company’s total assets, and the company’s growth.

In the efficiency measurement method, Feng and Wang (2015) applied factor analysis and data envelopment analysis (DEA) to evaluate the software and information technology services industry performance of 31 Chinese provinces [17]. Feng and Chen (2015) used stochastic frontier analysis (SFA) method to measure industrial innovation efficiency; empirical results showed that increasing the number of R&D personnel could further improve the efficiency of industrial innovation in China [18]. Tong and Zhu (2015) constructed an input-oriented model to measure the operating efficiency of 32 listed companies in the information technology industry in Shanghai and Shenzhen city [19]. Xiao, Shi, and Zhang (2020), used the analytic hierarchy process (AHP) and entropy weight method, built an index system, and evaluated the innovation ability of Chinese listed companies. The empirical results showed that factors such as patent quality, R&D investment ratio, undergraduate and above staff ratio are more important [20]. The purpose of Fathi (2021) is to examine the energy, environmental, and economic (E3) efficiency in fossil fuel exporting countries during 2015–2017, using traditional Data Envelopment Analysis (DEA) and a bargaining game cross-efficiency DEA approach [21]. Zhen and Yang (2022) use a panel data model technique to examine the dependence structure of green finance, energy efficiency, and CO emissions [22].

This paper has the following values and innovations. From the perspective of research objects, most scholars’ research on the software and information technology service industry tends to focus on macro industrial research, with less evaluation on innovation efficiency at the micro level. Zhang, Zhang, and Bai just compare the total factor productivity and its decomposition efficiency in software and information technology services from a macroscopic perspective [23]. This paper selects 80 listed companies in the industry as the research object and takes environmental variables into account more comprehensively based on both micro and macro perspectives. In terms of research methods, Zuo and Guo constructed a two-stage hybrid network DEA method to measure the innovation and entrepreneurship efficiency of mass innovation spaces in 30 provinces and cities. This method does not exclude the influence of external environmental factors and random factors [24]. Three-stage DEA has greater advantages than traditional DEA. It comprehensively uses the advantages of parametric and non-parametric methods, overcomes the limitations, and provides a theoretical basis and method for systematically evaluating the innovation efficiency of software and information technology service enterprises. In addition, DEA itself has unique advantages in dealing with multiple input and output decision units, which can avoid secondary data processing. It can give full play to the advantages of the three-stage DEA. In the empirical analysis, Abdul A and Deb analyzed the relationship between the information technology industry and economic growth from a positive perspective [25]. We can determine the positive and negative directions of the impact of environmental variables, and whether the impact is significant, so that we can adjust the investment redundancy or insufficient investment, and the policies of relevant departments are also scientific.

2. Model and Methods

The evaluation of innovation efficiency of software and information technology service enterprises is suitable for the data envelopment analysis (DEA) method because of the multi-input and multi-output components. Moreover, the efficiency of enterprise innovation is affected by multiple external environments, and it must be stripped to obtain accurate and reliable efficiency values. With the help of the regression of stochastic frontier model (SFA), the influence of external environmental variables and random errors in the efficiency measure can be eliminated (Fried et al., 2002), so the three-stage DEA model is selected in this paper [26].

2.1. Three-Stage DEA Model

The three-stage DEA model consists of the following three stages described below.

Stage 1: DEA model

The DEA model includes the CCR model and the BCC model. Charnes, Cooper, and Rhodes (CCR) (1978a, 1979) introduced a ratio definition of efficiency, also called the CCR ratio definition, which generalizes the single-output to a single-input classical engineering-science ratio definition to multiple outputs and inputs without requiring preassigned weights. However, in terms of efficiency, the CCR model can only explain technical efficiency, but cannot explain pure technical efficiency and scale efficiency. Unlike CCR, the BCC model can account for technical efficiency, pure technical efficiency, and scale efficiency. In the actual production activities of enterprises, there is a state of increasing or decreasing returns to scale. Thus, this paper uses the BCC model proposed by Banker, Charnes, and Cooper (1984) [27]. The BCC model can quantify technical efficiency and scale efficiency based on the assumption of variable return to scale (VRS) to estimate enterprise innovation. In addition, the calculated technical efficiency value satisfies the following decomposition relationship.

$$TE = PTE \times SE. \tag{1}$$

Technical efficiency (TE) measures the overall efficiency of the decision-making units (DMU). The output is the largest when the input is certain, or the input is the smallest when the output is certain. Pure technical efficiency (PTE) measures whether the allocation of various input elements is fully utilized and reflects the technical management level of an enterprise. Scale efficiency (SE) measures whether the input and output of DMU are in the best state of scale returns, that is, when the input increases, the "speed" of output increase is the largest. In the first stage of this paper, the input-oriented BCC model is selected to calculate the technical efficiency, pure technical efficiency, and scale efficiency of each DMU. The model can be defined as below.

$$min\left[\theta - \varepsilon\left(e^T s^+ + \hat{e}^T s^-\right)\right]$$
$$s.t.\begin{cases}\sum\limits_{i=1}^{n} \lambda_i x_i + s^- = \theta x_0 \\ \sum\limits_{i=1}^{n} \lambda_i y_i - s^+ = y_0 \\ \sum\limits_{i=1}^{n} \lambda_i = 1, \lambda_i \geq 0, i = 1, 2, \cdots, n \\ s^+ \geq 0, s^- \geq 0, \theta \text{ unlimited.}\end{cases} \tag{2}$$

where x_i and y_i are the input vectors group and the output vectors group of the ith of DMU respectively; λ is weight coefficient; s^- is the remaining variable, and s^+ is the relaxation variable; ε is the non-Archimedes infinitesimal; θ is the effective value of the DMU. Assuming that θ^0, λ_i^0, $i = 1, 2, \ldots, n$, s^{0+}, s^{0-} are the optimal solutions of Formula (2), then $e^T s^{0+}$ means that the input is reduced from x_0 to θx_0, and the sum of some input items that need to be reduced, $\hat{e}^T s^{0-}$ indicates the sum of insufficient output.

Stage 2: SFA regression model

The slack variables generated in the first stage are composed of three effects: environmental factors, management inefficiency, and random errors. Thus, this involves building a similar SFA model to eliminate the influence of environmental variables and random errors so that it only retains the slack of inputs caused by management inefficiency, and all DMUs are under an identical operating environment. The slacks of inputs as dependent variables and environmental variables as independent variables in the SFA model are shown in Formula (3).

$$S_{ni} = f(z_i; \beta^n) + v_{ni} + u_{ni} \ (i = 1, 2, \cdots, I; n = 1, 2, \cdots, N) \tag{3}$$

where S_{ni} denotes the slacks of nth input of ith DMU; $f(z_i; \beta^n)$ is stochastic frontier function generally taking a liner from representing the effect of the environmental factors to input Slacks, z_i and β^n are respectively expressed as environment variables and their corresponding parameter vectors; $v_{ni} + u_{ni}$ is hybrid error,v_{ni} and u_{ni} are independent and unrelated, $v_{ni} \in N\left(0, \sigma_{vn}^2\right)$ is random errors, and $u_{ni} \in N^+\left(0, \sigma_{un}^2\right)$ refers to the management inefficiency.

Before the input adjustment, it is necessary to separate the effects of random disturbance $\hat{E}(v_{ni}|v_{ni} + u_{ni})$ from management inefficiency $\hat{E}(u_{ni}|v_{ni} + u_{ni})$ by using the maximum likelihood estimation parameters (β^n,σ^2,γ) of SFA regression [28]. The method is as follows:

$$\hat{E}(v_{ni}|v_{ni} + u_{ni}) = S_{ni} - f(z_i; \hat{\beta}^n) - \hat{E}(u_{ni}|v_{ni} + u_{ni}) \text{ and } \hat{E}(u_{ni}|v_{ni} + u_{ni}) = \sigma_* \left[\frac{\varphi\left(\frac{\varepsilon_i \lambda}{\sigma}\right)}{\Phi\left(\frac{\varepsilon_i \lambda}{\sigma}\right)} + \frac{\varepsilon_i \lambda}{\sigma}\right]. \tag{4}$$

where $\sigma_* = \frac{\sigma_u \sigma_v}{\sigma}$, $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$, and $\lambda = \frac{\sigma_u}{\sigma_v}$ ($\gamma = \frac{\sigma_u^2}{\left(\sigma_u^2 + \sigma_v^2\right)}$), φ and Φ represent the density function and distribution function that follow the normal distribution, respectively.

Finally, all DMUs can be adjusted to the same external environment and level of luck by the formula as follows.

$$X_{ni}^A = X_{ni} + \left[max(z_i \hat{\beta}^n) - z_i \hat{\beta}^n\right] + \left[max(\hat{v}_{ni}) - \hat{v}_{ni}\right]. \tag{5}$$

where X_{ni}^A is the new input after X_{ni} adjusted, $\left[max\left(z_i \hat{\beta}^n\right) - z_i \hat{\beta}^n\right]$ represents the adjusted environment variables, and $[max(\hat{v}_{ni}) - \hat{v}_{ni}]$ represents the same level of luck.

Stage 3: Adjusted DEA model

The adjusted input value and the original output value are substituted into the DEA-BCC model again, and the results would be more objective and accurate to reflect the situation of enterprise efficiency.

2.2. Variable Selection

2.2.1. Innovation Input and Output Indicators

According to the previous studies (Han, Ge, and Cheng, 2015 [29]; Qu, Song, and Yu, 2018 [30]; Qi, Zhao, and Li, 2018 [31]; Wang, Ji, and Wu, 2019 [32]), the selection of indicators for evaluating the efficiency of listed companies in China comprehensively considers three aspects: human, financial, and material, following the principles of system, science, objectivity, and operation. Finally, four input indicators and five output indicators are identified, which are influential and vital for innovation efficiency measurement. All indicators are shown in Table 1.

Table 1. The input and output indicators of enterprise innovation efficiency.

Types	Indicators		Description
Innovation input	R&D input	R&D personnel	Number of personnel involved in R&D
		R&D expenditure	Total R&D investment
	Production input	Labor capital	Total number of employees
		Productive capital	Net fixed assets at the end of the year
Innovation output	Knowledge creation	Patents	Number of patents for invention granted
	Economic benefit	Increase rate of main business revenue	Growth of the difference of operating income between this year and last year
		Net profit	Net profit of enterprise at the end of year
		Technology assets	Proportion of intangible assets to total assets
		Capital accumulation rate	Ratio of growth to the owner's equity at the beginning of the year

Innovation input indicators include R&D input and production input. R&D personnel are the most direct and fundamental innovation production factors of an enterprise. The competition of the company's core technology is supported by the competition of talented individuals with professional knowledge and experience. R&D expenditure is another important production factor in enterprise innovation. Under the same conditions, greater investment can not only provide financial security for R&D and increase the probability of success, but also attract high-level talented individuals to gather and stimulate their enthusiasm for innovation. Labor capital is another major investment in innovative human resources. Whatever software products or information technology service should be completed by employees, such as production or promotion and application, which is particularly important for the company to generate economic benefits. Productive capital is composed of the higher-quality equipment and the technical platform with good performance, which has a certain auxiliary effect on the work efficiency of R&D personnel.

Innovation output indicators include knowledge creation and economic benefits. Patents are a direct measure of the output of knowledge creation integration. The patent that best reflects the level of innovation efficiency of the company is the invention patent. The increase rate of main business revenue represents the market occupation capacity of the company to a certain extent, reflecting its software products or the economic benefits generated by the service. Managers can evaluate the suitability of the research and development results based on this factor, and predict whether it has growth and is necessary to continuous research and development. Net profit is an essential indicator of the company's profitability, which reflects the enterprise's operating efficiency and largely affects the investment of R&D. Technology assets reflect the overall quality level of assets. Contrary to tangible assets, intangible assets determine the future development of the enterprise trend and represent the dynamic competitiveness of an enterprise. The expansion and reproduction of an enterprise is inseparable from the accumulation of capital. The greater the rate of capital accumulation, the faster the increase in owner's equity, so the enterprise can invest more R&D expenditure for innovation activities.

2.2.2. Environmental Variables

Environment variables refer to the factors beyond an enterprise's control that affect innovation efficiency. Based on the previous studies (Aboal et al., 2015 [33]; Wang & Wang, 2016 [34]; Sun, Guo & Xiao, 2016 [35]; Qu, Song & Yu, 2018; Wang, Fu, & Zhang, 2019 [36]; Dou, Hao, & Fang, 2019 [37]) following the principle of "separation assumption" (Léopold Simar & Paul W. Wilson, 2007 [38]) from the macro and micro perspective, eight environmental variables are selected to incorporate into the model. Each of these variables are specified as follows:

(1) Company age, expressed by business registration time to the reporting period; (2) Personnel quality, expressed by the proportion of the company's workforce with a master's degree and above; (3) Market share, expressed by the ratio of the main business income of a single company to the sum of the main business income of all sample companies; (4) Enterprise scale, expressed by a logarithm of the company's total assets; (5) Economic level, expressed by the gross regional product (GDP) of the city where the enterprise is located; (6) Open level, expressed by the amount of imports and exports in the province where the enterprise is located; (7) Government subsidies, expressed by the total amount of government subsidies at the end of the year; (8) Loan level, expressed by the loan balance of the financial institution in the province where the enterprise is located.

3. Empirical Analysis

3.1. Data Sources

The data covers 80 software and information technology services companies in China from 2017 to 2019, with a one-year lag. Since the outbreak of COVID-19 in 2019, the pandemic has dealt a blow to various industries. The information technology industry has also taken a hit and the effect has continued to the present. Therefore, the data from 2019 and beyond should not be used as reference material. The data from 2017 and 2018 are available and complete, relatively. All the data of input and output indicators are acquired from China's CSMAR database (http://www.gtarsc.com/ (accessed on 8 September 2022)). Considering the non-negative nature of DEA data, this paper employed Formula (6) to standardize negative indicators (growth rate, cumulative profit, net profit, etc.) and adjusted them to the value range of [0.1, 1]. The descriptive statistics of indicators are shown in Table 2. The environmental variables were obtained from the National Bureau of Statistics (http://www.stats.gov.cn/ (accessed on 8 September 2022)), Wind financial database (https://www.wind.com.cn/ (accessed on 8 September 2022)) and from the statistical yearbooks of provinces and cities. All the above data sources show reliability and authenticity.

$$\begin{cases} y_{ij} = 0.1 + \frac{x_{ij}-m_j}{M_j-m_j} \times 0.9 \\ m_j = min(x_{ij}), M_j = max(x_{ij}) \end{cases} \tag{6}$$

Table 2. Descriptive statistics of innovation input and output data.

Variables	Units	Year	Minimum	Maximum	Mean	Standard Deviation
R&D personnel	Person	2017	17	14,839	960	1798.089
		2018	29	13,866	1110	1762.533
R&D expenditure	10,000 yuan	2017	56.600	88,911.370	16,653.167	20,587.319
		2018	924.370	107,222.330	20,201.027	23,888.920
Labor capital	Person	2017	205	19,085	2473	2824.151
		2018	110	16,706	3211	3157.617
Productive capital	10,000 yuan	2017	277.490	181,237.910	25,795.754	31,470.88
		2018	173.980	522,329.410	41,188.444	67,873.624
Patents	Piece	2017	1	182	18	32.325
		2018	1	516	22	61.675
Increase rate of main business revenue	-	2017	0.100	1.000	0.371	0.152
		2018	0.100	1.000	0.191	0.096
Net profit	10,000 yuan	2017	0.100	1.000	0.609	0.095
		2018	0.100	1.000	0.219	0.101
Technology assets	%	2017	0.059	10.725	3.247	2.352
		2018	0.046	10.430	3.242	2.208
Capital accumulation rate	-	2017	0.100	1.000	0.220	0.118
		2018	0.100	1.000	0.299	0.166

3.2. Results Analysis

3.2.1. Three-Stage DEA Results

Stage 1: DEA model results and analysis

In this paper, software Deap2.1 is used to evaluate the enterprise innovation efficiency of software and information technology services in China. The detailed results are shown in Table 3. According to the results in Table 3, in 2017 the means of innovation efficiency, pure technical efficiency, and scale efficiency are 0.492, 0.606, and 0.835. The corresponding data for 2018 are 0.688, 0.758, and 0.903, respectively, which is slightly improved. Obviously, most companies achieved non-effective efficiency in both 2017 and 2018, which was caused by pure technical efficiency and scale efficiency, and the impact of pure technical efficiency was greater than scale efficiency overall.

Table 3. Unadjusted Innovation efficiency from 2017 to 2018.

Stock Code	Stock Abbreviation	2017				2018			
		TE	PTE	SE	RTS	TE	PTE	SE	RTS
000555	Digital China Information	0.069	0.07	0.994	-	0.125	0.13	0.958	drs
000662	Teamax	1	1	1	-	1	1	1	-
000682	Dongfang Electronics	0.202	0.203	0.998	-	0.354	0.37	0.957	drs
000997	Newland	0.172	0.511	0.336	drs	0.403	1	0.403	drs
002063	YGsoft	0.105	0.109	0.963	drs	0.528	0.563	0.938	drs
002123	Montnets Group	0.415	0.612	0.677	drs	0.372	0.596	0.624	drs
002148	Bewinner Tech	0.848	0.909	0.933	drs	0.961	1	0.961	drs
002153	Shiji Information	0.251	0.663	0.378	drs	0.367	0.435	0.843	drs
002230	Iflytek	0.326	1	0.326	drs	0.315	0.346	0.909	drs
002232	Qiming Information	0.28	0.305	0.916	drs	0.304	0.304	0.999	-
002253	Wisesoft	0.875	1	0.875	drs	1	1	1	-
002261	Talkweb Information	0.24	0.299	0.803	drs	0.32	0.334	0.959	drs
002268	Westone	0.334	0.336	0.993	drs	1	1	1	-
002280	Lianluo Interactive	1	1	1	-	1	1	1	-

Table 3. *Cont.*

Stock Code	Stock Abbreviation	2017				2018			
		TE	PTE	SE	RTS	TE	PTE	SE	RTS
002298	Sinonet	0.916	0.962	0.952	drs	0.923	1	0.923	irs
002322	Ligong Environment	0.344	0.35	0.983	irs	0.487	0.623	0.781	drs
002331	Wantong Technology	0.83	1	0.83	drs	1	1	1	-
002368	Taiji	0.299	1	0.299	drs	0.411	0.427	0.962	drs
002373	CTFO	0.574	0.884	0.65	drs	1	1	1	-
002380	SCIYON	0.365	0.37	0.985	irs	0.386	0.44	0.876	drs
002401	COSCO SHIP TECH	0.689	0.698	0.987	irs	0.916	0.916	1	-
002405	NavInfo	0.16	0.254	0.629	drs	0.65	1	0.65	drs
002410	Glodon	0.081	0.181	0.449	drs	0.322	0.528	0.609	drs
002417	SUNA	1	1	1	-	1	1	1	-
002421	Das Intellitech	0.392	0.43	0.91	drs	0.596	0.599	0.996	drs
002474	Rongji Software	0.62	0.926	0.67	drs	1	1	1	-
002544	Gci Sciand Tech	0.68	0.705	0.964	drs	0.668	1	0.668	drs
002602	Century Huatong	0.134	0.603	0.223	drs	0.475	0.564	0.842	drs
002609	Jieshun Science and Technology	1	1	1	-	1	1	1	-
002649	Beyondsoft	0.168	0.168	0.994	drs	0.248	0.281	0.88	drs
002657	Sinodata	1	1	1	-	1	1	1	-
300010	Lanxum	0.34	0.345	0.985	drs	0.372	0.387	0.962	drs
300017	Wangsu Sci and Tech	0.21	1	0.21	drs	0.586	0.784	0.747	drs
300020	Enjoyor	0.825	0.828	0.996	drs	1	1	1	-
300036	Supermap Software	0.286	0.298	0.96	drs	0.426	0.498	0.854	drs
300044	Sunwin	0.737	0.754	0.978	drs	1	1	1	-
300047	Tianyuan Dic	0.213	0.252	0.846	drs	0.584	0.604	0.965	drs
300050	Dingli Communications	0.525	0.597	0.879	drs	0.803	0.953	0.843	drs
300074	Avcon	0.417	0.42	0.992	irs	0.645	0.649	0.994	irs
300075	Egova	0.553	0.624	0.886	drs	1	1	1	-
300085	Infogem	0.762	1	0.762	drs	1	1	1	-
300098	Gosun	0.509	0.52	0.979	drs	0.77	1	0.77	drs
300150	Century Real	1	1	1	-	1	1	1	-
300167	DVX	1	1	1	-	0.673	0.673	1	-
300168	Wonders Information	0.129	0.242	0.533	drs	0.294	0.354	0.831	drs
300183	Eastsoft	0.77	1	0.77	drs	0.572	0.662	0.864	drs
300188	Meiya Pico	0.512	0.514	0.996	irs	0.593	0.609	0.974	drs
300209	Tianze Info	0.539	1	0.539	drs	0.898	0.904	0.994	irs
300212	E-hualu	0.966	0.968	0.998	irs	0.679	0.835	0.813	drs
300229	TRS	0.301	0.305	0.987	drs	0.312	0.334	0.935	drs
300250	CNCR-IT	0.856	0.861	0.993	irs	0.843	1	0.843	drs
300264	AVIT	1	1	1	-	1	1	1	-
300271	Thunisoft	0.287	0.86	0.334	drs	1	1	1	-
300275	Massci	0.618	0.625	0.989	irs	1	1	1	-

Table 3. *Cont.*

Stock Code	Stock Abbreviation	2017				2018			
		TE	PTE	SE	RTS	TE	PTE	SE	RTS
300287	Philisense	0.333	0.345	0.965	drs	0.409	0.625	0.654	drs
300290	Bringspring	0.625	0.642	0.974	irs	0.509	0.54	0.943	drs
300297	Bluedon	0.33	0.461	0.715	drs	1	1	1	-
300299	Fuchun Technology	0.619	0.652	0.949	irs	1	1	1	-
300302	Toyou Feiji	1	1	1	-	1	1	1	-
300311	Surfilter	0.352	0.357	0.986	irs	0.484	0.487	0.993	drs
300312	Boomsense Technology	0.392	0.407	0.963	irs	0.783	0.899	0.871	irs
300324	Watertek Information	0.865	1	0.865	drs	0.443	0.768	0.577	drs
300330	Huahongjt	1	1	1	-	1	1	1	-
300339	Hoperun Software	0.139	0.159	0.874	drs	0.187	0.188	0.999	-
300349	Goldcard Smart	0.474	0.488	0.97	irs	0.501	0.802	0.625	drs
300352	VRV Software	0.363	0.38	0.955	irs	0.411	0.443	0.929	drs
600406	Nari	1	1	1	-	1	1	1	-
600410	Teamsun	0.299	0.299	0.999	-	0.326	0.346	0.944	drs
600536	China National Software	0.204	0.647	0.316	drs	1	1	1	-
600570	Hundsun	0.038	0.04	0.947	irs	0.289	0.496	0.583	drs
600571	Sunyard	0.289	0.352	0.821	drs	1	1	1	-
600588	Yonyou Network	0.199	0.594	0.336	drs	0.703	0.704	0.998	drs
600602	INESA Intelligent	0.147	0.154	0.953	drs	0.495	0.511	0.969	drs
600718	Neusoft	0.155	1	0.155	drs	0.549	0.607	0.905	drs
600728	PCI-Suntek Technology	0.663	0.681	0.974	drs	0.814	1	0.814	drs
600756	Inspur Software	0.321	0.33	0.973	irs	0.88	0.903	0.974	irs
600797	Insigma	0.19	0.206	0.921	drs	0.698	1	0.698	drs
600845	Baosight	0.327	0.344	0.95	drs	0.409	0.629	0.65	drs
600850	East-China Computer	0.213	0.221	0.962	drs	1	1	1	-
601519	Great Wisdom	0.134	0.136	0.983	drs	1	1	1	-
	mean	0.492	0.606	0.835		0.688	0.758	0.903	

Note: RTS is return to scale, "irs", "drs", and "-" indicate that the return to scale is increasing, decreasing, and constant.

According to the value differences, enterprise efficiency can be divided into five categories from good to bad in stage one: Best (1), Good (0.8–1), General (0.4–0.8), Bad (0.2–0.4), Worse (less than 0.2).

As shown in Table 4, 11 (13.75%) and 27 (33.75%) companies were viewed as "Best" in 2017 and 2018, which had achieved DEA effectively and were at the frontier of efficiency. Eight (10%) companies were viewed as "Good" during these two years. The number of "General" companies are 19 (23.75%) and 29 (36.25%), respectively. The number of "Bad" and "Worse" companies are 42 (52.5%) in 2017 and 16 (20%) in 2018. These companies were not on the frontier of efficiency, were non-DEA effective, and accounted for 86.25% (2017) and 66.25% (2018). The number of companies with increasing and decreasing returns to scale is 16 and 50 in 2017, respectively, while only three companies (Digital China Information, Dongfang Electronics, Teamsun) kept constant returns to scale. While in 2018, the companies of returns to scale with increasing, decreasing, and constant is five, forty-four, and four (Qiming Information, COSCO SHIP TECH, Shenzhen DVX, HopeRun Software).

Table 4. Classification of innovation.

Efficiency Value	Viewed	2017			2018		
		Number	Weight	Accumulation	Number	Weight	Accumulation
1	Best	11	13.75%	13.75%	27	33.75%	33.75%
0.8–1	Good	8	10%	23.75%	8	10%	43.75%
0.4–0.8	General	19	23.75%	47.5%	29	36.25%	80%
0.2–0.4	Bad	27	33.75%	81.25%	14	17.5%	97.5%
Below 0.2	Worse	15	18.75	100%	2	2.5%	100%

In summary, more than 80% of companies still had room to improve innovation efficiency in 2017, this number decreased slightly in 2018, but it also exceeded 60%, indicating that there is huge room for improvement. Further, because of the bigger impact of the low pure technical efficiency, enterprises should pay attention to the internal management capacity for innovation and take measures to improve the current technical level.

Stage 2: SFA regression empirical results

Results in stage one ignored the influence of external environmental variables and random errors and should be eliminated. In stage two, this paper used the standardized environmental variables as dependent variables and the input slacks variable (the difference between original input value and target input value, namely, input redundancy mentioned below) as independent variables, and established the SFA regression model year by year. Having calculated the parameters with Frontier 4.1 software and decomposed the value of slacks in Excel, the regression results of 2017 and 2018 are listed in Tables 5 and 6.

Table 5. Results of SFA regression in 2017.

Independent Variable	Dependent Variable			
	R&D Personnel	R&D Expenditure	Labor Capital	Productive Capital
Constant	−449.243 *** (−77.019)	−10,939.911 *** (−116.349)	−1449.652 *** (−14.708)	−11,306.013 *** (−32.350)
Company age	9.089 *** (3.492)	−173.851 *** (−3.163)	195.430 ** (2.438)	−8925.661 *** (−26.196)
Personnel quality	−2138.307 *** (−460.008)	−36,624.971 *** (−587.090)	−4963.199 *** (−50.769)	−26,647.864 *** (−343.528)
Market share	873.250 *** (79.746)	921.685 *** (9.366)	2643.736 *** (16.715)	11,597.609 *** (19.433)
Enterprise scale	−392.179 *** (−50.063)	−4181.496 *** (−34.411)	−592.891 ** (−2.608)	20,503.585 *** (26.325)
Economic level	472.652 *** (63.058)	9466.675 *** (171.173)	708.081 *** (43.852)	−1990.401 ** (−2.632)
Open level	343.037 *** (104.556)	−6039.677 *** (−231.403)	−1606.920 *** (−14.044)	−7341.693 *** (−9.471)
Government subsidies	1141.269 *** (111.713)	32,314.221 *** (301.287)	1252.126 *** (9.587)	−2641.272 *** (−7.889)
Loan level	−82.737 *** (−19.136)	10,778.433 *** (202.200)	2756.663 *** (189.694)	10,222.989 *** (15.871)
σ^2	1,149,531.9 *** (1,149,528.200)	364,634,140 *** (364,636,420.000)	6,925,095 *** (6,920,834.800)	860,065,340 *** (860,030,210.000)
γ	1.000 *** (1714.853)	1.000 *** (913,933.430)	1.000 *** (61,254.121)	0.998 *** (660.729)
Log Likelihood	−619.184	−846.319	−690.790	−879.671
LR value	36.981 ***	41.052 ***	35.013 ***	39.224 ***

Note: The significance level without * is 10%, and **, *** indicate the significance level at 5% and 1% respectively. The data in brackets are t statistics.

Table 6. Results of SFA regression in 2018.

Independent Variable	Dependent Variable			
	R&D Personnel	R&D Expenditure	Labor Capital	Productive Capital
Constant	−1209.960 *** (−7.004)	−12,371.326 *** (−12,371.326)	−3459.980 *** (−174.902)	−28,117.305 *** (−56.969)
Company age	863.163 *** (12.566)	7670.708 *** (7670.708)	1462.406 *** (58.021)	−1023.185 *** (−6.626)
Personnel quality	−1233.793 *** (−77.089)	−9511.196 *** (−9511.196)	−1032.850 *** (−57.733)	13,376.488 *** (49.567)
Market share	356.320 *** (39.600)	−350.760 *** (−350.760)	614.939 *** (13.334)	−9845.714 *** (−27.456)
Enterprise scale	1124.405 *** (15.043)	6529.901 *** (6529.901)	4216.427 *** (118.084)	53,825.596 *** (190.341)
Economic level	85.186 *** (2.798)	348.332 *** (348.332)	163.013 ** (2.430)	−1050.552 * (−1.860)
Open level	903.947 *** (95.294)	4800.742 *** (4800.742)	393.361 *** (15.966)	18,828.533 *** (47.191)
Government subsidies	−188.349 *** (−27.141)	8033.309 *** (8033.309)	−943.639 *** (−26.576)	−15,795.454 *** (−52.235)
Loan level	−1074.150 *** (−33.607)	−8265.985 *** (−8265.985)	−553.614 *** (−19.701)	−26,915.543 *** (−63.362)
σ^2	4,654,296.2 *** (4,654,322.700)	498,709,480 *** (498,709,480.000)	13,453,517 *** (13,453,498.000)	836,568,500 *** (836,566,830.000)
γ	1.000 *** (6857.332)	1.000 *** (33.937)	1.000 *** (3389.344)	0.994 *** (222.050)
Log Likelihood	−661.099	−859.165	−711.393	−884.970
LR value	61.367 ***	36.637 ***	43.157 ***	26.408 ***

Note: *, **, *** indicate the significance level at 10%, 5%, and 1% respectively. The data in brackets are t statistics.

The influence of various environmental variables on input slacks (R&D personnel, R&D expenditure, labor capital, and productive capital) can be determined by the positive or negative value of the regression coefficient. In the case of the regression coefficient being a positive value, continuing to increase the input will increase its redundancy, which is not conducive to enterprise innovation; on the contrary, in the case of the regression coefficient being a negative value, continuing to increase the input will reduce redundancy, which is advantageous for enterprise innovation. According to this principle, the coefficient value of each environmental variable can be analyzed year by year, and then it can be judged how to adjust the input to improve the innovation efficiency of the enterprise.

From Tables 5 and 6, all tests of environmental variables basically reach the significance level of 1%. The value of LR, σ^2, and γ also pass the significance test of 1%. Meanwhile, each regression model value of γ approaches one. These results demonstrate that the selected environmental variables are reasonable and have significant impacts on the innovation efficiency of sample companies, and SFA for regression analysis is very suitable, while the dominant impact of innovation efficiency is management inefficiency while random factors are insignificant.

(1) Company age. In 2017, the company age of sample companies is positively correlated with input slack variables such as R&D personnel and labor capital. On the contrary, they are negatively correlated with input slack variables such as R&D expenditure and labor capital. In 2018, except for productive capital with a negative correlation, others are positively correlated. It indicates that the older companies with an accumulation of technology and experience have a better use of R&D equipment. However, the fund of R&D expenditure has a lower utilization rate, and so does manpower investment. To a certain extent, it explains why the innovation efficiency of overall enterprises is not high.

(2) Personnel quality. The personnel quality of most companies is negatively correlated with the slack variables of each input, behaving positively correlated with productive capital only in 2018. It indicates that the greater the proportion of employees with a master's

degree and above, the easier it is to enhance employees' sense of identity with the company and maintain a good R&D atmosphere, thereby gradually increasing the utilization rate of both manpower and financial resources. Regrettably, there will be some redundancy in the utilization of R&D or production equipment after the accumulation of high-level personnel.

(3) Market share. The market share of sample companies shows a negative correlation with R&D expenditure and productive capital input slack variables only in 2018. The rest of the time, especially in 2017, shows a positive correlation. With the accumulation of company main business income, the market share is increasing, and its position is becoming more and more stable. Therefore, it has become richer in talent recruitment, R&D investment, and equipment purchases. Inevitably, some redundancy is created in human, material, and financial resources. The overall innovation efficiency in 2017 is so low and inseparable from these factors.

(4) Enterprise scale. The enterprise scale is positively correlated with each input slack variable in 2018, while in 2017 it is only positively correlated with production capital; the rest is negatively correlated. It indicates that there is a small redundant space for R&D personnel, R&D expenditure, and enterprise employees when the enterprise scale is small, which basically realizes the high utilization of human and financial resources. However, a lack of experience requires introducing R&D talents and expanding the scale of employee recruitment when the enterprise scale expands. As a result, the rapid expansion has led to a mismatch of capabilities in various fields, causing multi-party redundancy. At this time, enterprises are in need of a firm foothold, so innovation efficiency is low.

(5) Economic level. From 2017 to 2018, the economic development level of the city where the company is located is positively correlated with R&D personnel, R&D expenditure, and labor capital, while productive capital is negatively correlated, but the significance level of the coefficient test is not high. It is easy to form an industrial cluster effect where the higher the regional economic development level, the more convenient the transportation and the higher the consumption levels. It is stacked growth in the aspects of manpower, material, and financial; the waste caused by this high investment is obvious compared with underdeveloped areas.

(6) Total imports and exports. The total of imports and exports only has a positive correlation with the slack variable of R&D personnel in 2017, and all shows a positive correlation in 2018. When opening up to the outside world is slow, there is less technology introduction and talent and technology exchanges; on the contrary, when expanding its degree of opening up, the dependence on foreign technology and capital investment both increase, and the passion for independent research and development decreases.

(7) Government subsidies. There is a different correlation between 2017 and 2018 about government subsidies for enterprise innovation. Table 5 reflects a positive correlation on many inputs such as R&D personnel, R&D expenditure, and labor capital, while it is the opposite in 2018, and has a negative correlation on inputs except R&D expenditure. It indicates that government has achieved a better expectation effect in supporting the innovation of enterprises whereby the waste of other inputs has been reduced except redundancy in R&D expenditure. However, it seems to require a buffer period for the enterprise, the short-term rate of utilization is lower and easier to cause redundancy in funds.

(8) Loan level. The level of financial development has a different effect on various input redundancies in 2017 and 2018. Except that the impact of R&D personnel input redundancy is negatively correlated, R&D expenditure, labor capital, and productive capital are all positively related. On the contrary, each of them shows a negative correlation in 2018. It indicates that there is a growing loan balance of the financial institution in the province where the company is located. The redundancy of R&D personnel would be reduced in 2017; oppositely, the utilization rate of various inputs would be fully improved in 2018.

In brief, R&D personnel and labor capital were the most heavily invested, followed by R&D expenditure, and finally productive capital investment in 2017. Its situation changed slightly in 2018, the specific performance is redundancy of inputs which is more focused on R&D personnel, R&D expenditure, and labor capital, with only productive capital having less redundancy. Owing to environmental variables which had important impacts on the innovation efficiency of sample companies, companies in each evaluation unit were in different external environments and did not have the same level of luck, which led to low innovation efficiency of the entire enterprise. The original input must therefore be adjusted.

Stage 3: Adjusted DEA model results and analysis

After obtained the adjustment input in stage two, we ran the BCC model again to calculate the enterprise innovation efficiency of the software and information technology service industries. The results are summarized and showed in Table 7.

Table 7. Adjusted innovation efficiency from 2017 to 2018.

Stock Code	Stock Abbreviation	2017				2018			
		TE	PTE	SE	RTS	TE	PTE	SE	RTS
000555	Digital China Information	0.53	0.55	0.964	irs	0.263	0.264	0.999	-
000662	Teamax	1	1	1	-	1	1	1	-
000682	Dongfang Electronics	0.483	0.5	0.967	irs	0.495	0.508	0.975	irs
000997	Newland	0.645	0.802	0.804	drs	0.534	1	0.534	drs
002063	YGsoft	0.547	0.553	0.99	drs	0.5	0.503	0.994	irs
002123	Montnets Group	0.704	0.825	0.853	drs	1	1	1	-
002148	Bewinner Tech	0.803	0.887	0.906	drs	0.829	0.83	0.999	drs
002153	Shiji Information	0.7	0.924	0.757	drs	0.637	0.778	0.819	drs
002230	Iflytek	0.638	1	0.638	drs	0.883	1	0.883	drs
002232	Qiming Information	0.407	0.416	0.978	irs	0.622	0.634	0.981	irs
002253	Wisesoft	0.512	0.512	0.999	irs	1	1	1	-
002261	Talkweb Information	0.579	0.61	0.948	drs	0.737	0.738	0.999	irs
002268	Westone	0.384	0.397	0.967	irs	0.615	0.616	0.999	irs
002280	Lianluo Interactive	1	1	1	-	1	1	1	-
002298	Sinonet	0.933	1	0.933	drs	1	1	1	-
002322	Ligong Environment	0.755	0.805	0.939	irs	0.627	0.629	0.996	drs
002331	Wantong Technology	0.776	0.785	0.989	irs	1	1	1	-
002368	Taiji	0.972	1	0.972	drs	0.745	0.773	0.964	drs
002373	CTFO	0.987	1	0.987	drs	1	1	1	-
002380	SCIYON	0.575	0.588	0.977	irs	0.724	0.724	1	-
002401	COSCO SHIP TECH	0.602	0.634	0.95	irs	0.789	0.801	0.985	irs
002405	NavInfo	0.744	0.764	0.973	irs	0.653	0.671	0.973	irs
002410	Glodon	0.461	0.605	0.762	drs	0.433	0.583	0.743	drs
002417	SUNA	0.868	0.951	0.913	irs	0.423	0.489	0.866	irs
002421	Das Intellitech	0.859	0.936	0.918	drs	0.792	0.809	0.98	drs
002474	Rongji Software	0.755	0.791	0.955	irs	1	1	1	-
002544	Gci Sciand Tech	1	1	1	-	0.628	0.646	0.972	irs
002602	Century Huatong	0.672	0.853	0.787	drs	0.515	0.609	0.846	drs
002609	Jieshun Science and Technology	1	1	1	-	1	1	1	-
002649	Beyondsoft	0.609	0.624	0.976	irs	0.461	0.464	0.994	drs

Table 7. *Cont.*

Stock Code	Stock Abbreviation	2017				2018			
		TE	PTE	SE	RTS	TE	PTE	SE	RTS
002657	Sinodata	1	1	1	-	1	1	1	-
300010	Lanxum	1	1	1	-	1	1	1	-
300017	Wangsu Sci and Tech	0.615	1	0.615	drs	0.876	1	0.876	drs
300020	Enjoyor	0.858	0.867	0.99	irs	1	1	1	-
300036	Supermap Software	0.643	0.656	0.98	drs	0.677	0.699	0.969	drs
300044	Sunwin	0.501	0.501	1	-	0.892	0.892	1	-
300047	Tianyuan Dic	0.632	0.634	0.998	drs	0.781	0.789	0.99	irs
300050	Dingli Communications	0.986	1	0.986	drs	0.908	0.928	0.979	Irs
300074	Avcon	0.858	0.858	1	-	0.659	0.682	0.967	irs
300075	Egova	1	1	1	-	0.922	0.924	0.998	irs
300085	Infogem	1	1	1	-	0.935	0.938	0.997	drs
300098	Gosun	0.893	0.905	0.987	drs	0.571	0.604	0.944	drs
300150	Century Real	0.912	0.937	0.974	irs	1	1	1	-
300167	DVX	1	1	1	-	0.741	0.752	0.986	irs
300168	Wonders Information	0.452	0.454	0.996	irs	0.615	0.657	0.936	drs
300183	Eastsoft	0.717	0.744	0.964	drs	0.726	0.889	0.817	drs
300188	Meiya Pico	0.609	0.618	0.985	irs	0.645	0.647	0.998	irs
300209	Tianze Info	1	1	1	-	1	1	1	-
300212	E-hualu	0.665	0.681	0.976	drs	1	1	1	-
300229	TRS	0.749	0.77	0.973	drs	0.635	0.637	0.997	irs
300250	CNCR-IT	1	1	1	-	0.751	0.755	0.994	irs
300264	AVIT	0.939	1	0.939	drs	0.837	0.849	0.985	irs
300271	Thunisoft	0.771	0.793	0.972	drs	1	1	1	-
300275	Massci	0.57	0.633	0.9	irs	0.792	0.86	0.921	irs
300287	Philisense	0.707	0.75	0.943	drs	0.706	0.769	0.918	drs
300290	Bringspring	0.612	0.652	0.939	irs	0.496	0.529	0.939	irs
300297	Bluedon	0.898	1	0.898	drs	1	1	1	-
300299	Fuchun Technology	0.73	0.771	0.947	irs	0.947	0.955	0.991	irs
300302	Toyou Feiji	0.787	0.801	0.983	irs	0.723	0.725	0.997	irs
300311	Surfilter	0.753	0.773	0.974	drs	0.725	0.726	0.999	irs
300312	Boomsense Technology	0.754	0.814	0.927	irs	0.605	0.656	0.922	irs
300324	Watertek Information	0.979	1	0.979	drs	1	1	1	-
300330	Huahongjt	0.6	0.662	0.907	irs	0.54	0.594	0.91	irs
300339	Hoperun Software	0.619	0.628	0.985	drs	0.41	0.41	1	-
300349	Goldcard Smart	0.872	0.895	0.975	irs	0.746	0.753	0.991	irs
300352	VRV Software	0.697	0.748	0.932	irs	0.651	0.676	0.963	irs
600406	Nari	1	1	1	-	1	1	1	-

Table 7. *Cont.*

Stock Code	Stock Abbreviation	2017				2018			
		TE	PTE	SE	RTS	TE	PTE	SE	RTS
600410	Teamsun	0.407	0.427	0.953	irs	0.591	0.602	0.982	irs
600536	China National Software	0.469	0.766	0.612	drs	1	1	1	-
600570	Hundsun	0.269	0.31	0.868	irs	0.393	0.412	0.956	irs
600571	Sunyard	0.797	0.823	0.97	irs	0.696	0.698	0.997	irs
600588	Yonyou Network	0.37	0.665	0.556	drs	1	1	1	-
600602	INESA Intelligent	0.563	0.642	0.877	drs	1	1	1	-
600718	Neusoft	0.416	1	0.416	drs	1	1	1	-
600728	PCI-Suntek Technology	0.945	0.97	0.974	irs	0.983	0.997	0.986	irs
600756	Inspur Software	0.559	0.584	0.957	irs	0.87	0.886	0.982	irs
600797	Insigma	0.622	0.622	1	-	0.674	0.678	0.994	drs
600845	Baosight	0.534	0.538	0.992	drs	0.392	0.532	0.738	drs
600850	East-China Computer	0.929	0.953	0.975	drs	1	1	1	-
601519	Great Wisdom	0.479	0.481	0.995	drs	0.973	0.988	0.985	drs
	mean	0.728	0.783	0.932		0.775	0.802	0.964	

Note: RTS is return to scale, "irs", "drs", and "-" indicate that the return to scale is increasing, decreasing, and constant.

As shown in Table 7, without the influence of the environmental variable, the mean enterprise innovation efficiency of software and information technology service is 0.728 (in 2017) and 0.755 (in 2018). The mean values of pure technical efficiency and scale efficiency have increased by varying degrees, the former from 0.783 to 0.802, and the latter from 0.932 to 0.964. Compared with the innovation efficiency value calculated in stage one, innovation efficiency and pure technical efficiency have been greatly improved within two years, and the scale efficiency has a small fluctuation range. By comparing the data of 2017 and 2018 in Table 7, the fluctuation of scale efficiency can be observed. It can be inferred that enterprises realized their problems and made adjustments and improvements. The further analysis of efficiency changes is as follows.

(1) Changes in innovation efficiency. Twelve companies had an innovation efficiency value of one in 2017, a year-on-year decrease of 9.1%, while the innovation efficiency of 60 companies had improved with an average increase of 158.75% year-on-year. In these companies, Digital China Information and Hundsun had the fastest improvement, an increase of more than 600%; Sinonet and Enjoyor improved less than 5%. The innovation efficiency value of six companies including Gci Science Tech and Lanxum increased to one. The innovation efficiency of fourteen companies had declined including Bewinner Tech, Wisesoft, and Wantong Technology, etc., and the largest declining companies were Wisesoft and Huahongit, which exceeded 40%. In addition, six companies including Teamax and Lianluo Interactive remained constant. Twenty-four companies had an innovation efficiency value of one in 2018, which was 11.1% lower than before the eliminated influence of the environmental variable. In other companies, the innovation efficiency of forty-two companies had improved, with an increase of 64.07% year-on-year, while the innovation efficiency of twenty-three companies had decreased. The largest declining companies had reached the rate of 57.7%, except for the companies SUNA and Huahongit. Others displayed a slow change trend, and 43.5% of the companies dropped by less than 10%. Fifteen companies maintained a constant value of innovation efficiency including Century Real, Thunisoft, and Bluedon, etc. Figures 1 and 2 denote the changes in innovation efficiency before and after adjustment in 2017 and 2018.

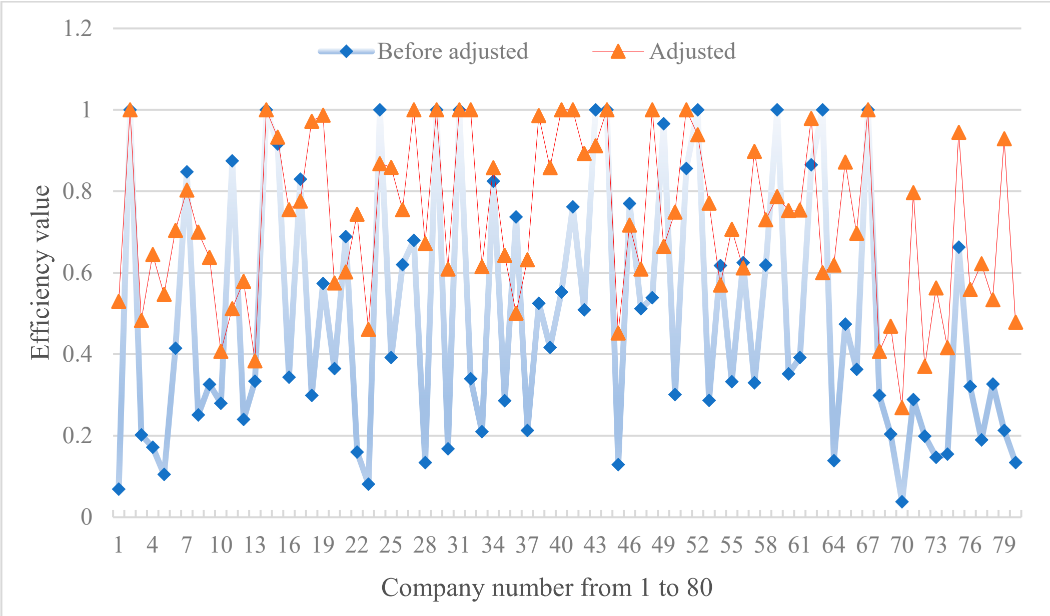

Figure 1. Changes in innovation efficiency before and after adjustment in 2017.

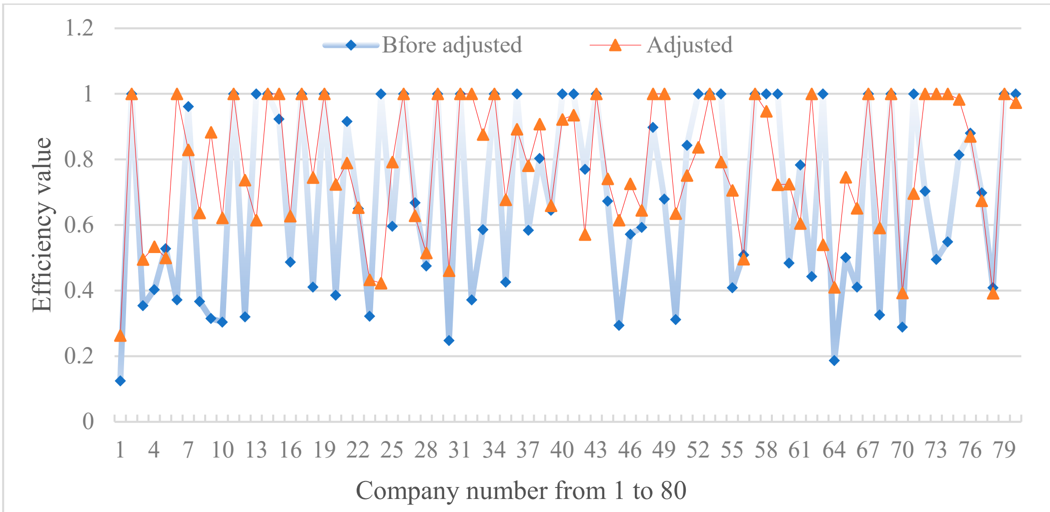

Figure 2. Changes in innovation efficiency before and after adjustment in 2018.

(2) Changes in pure technical efficiency. Fifty-three companies had improved pure technical efficiency which accounted for 66.25% of the samples in 2017. The actual level of Digital China Information and Hundsun was seriously underestimated. The pure technical efficiency of thirteen companies had fallen, and the biggest change was Wisesoft (48.8%), while fourteen companies remained constant. Thirty-five companies had improved pure technical efficiency, accounting for 43.75% of the samples in 2018, and six companies including Iflytek and Lanxum had improved by a large margin, all exceeding 103%. Precisely 57.14% of the companies have exceeded the average level. The pure technical efficiency of twenty-eight companies had decreased, with an average decrease of 18.73%, and SUNA reached a maximum value of 51.1%. In addition, seventeen companies remained constant in pure technical efficiency.

(3) Changes in scale efficiency. Forty-four companies saw scale efficiency increase by an average of 50.02% in 2017, whereby Century Huatong and Taiji had the largest increase, both exceeding 225%. Twenty-nine companies saw scale efficiency exhibit a slight decline, with an average value of only 3.56%. Seven companies maintained their scale efficiency

constant. The scale efficiency of forty-four companies increased by an average of 17.62% in 2018. Watertek Information, Hundsun, Montnets Group, and Goldcard Smart were four companies that had increased by a large margin with all exceeding 50%. Twenty-one companies had changed less than 10%. Twenty companies had slightly reduced scale efficiency, with an average fluctuation of 2.8%. The scale efficiency of sixtenn companies remained constant. In addition, the companies with constant returns to scale were fifteen (18.75%) in 2017 and twenty-eight (35%) in 2018. Nearly two-thirds of these companies are not at the optimal scale of innovation and have a lot of room for growth.

Based on the above analysis, it is concluded that pure technical efficiency and scale efficiency jointly lead to the current situation of low enterprise innovation efficiency, and pure technical efficiency has dominant influences on enterprise innovation in many companies. It indicates that most companies' current innovation scale does not match the optimal innovation scale. It is necessary to improve management level and technical capabilities and adjust the innovation scale. The empirical results show that after removing the influence of environmental factors and random errors, the adjusted innovation efficiency can better reflect enterprise innovation status.

3.2.2. Analysis of the Type of Enterprise Innovation

Software and information technology service companies with actual innovation efficiency levels can be divided into five types according to efficiency values (PTE and SE): Pioneer (PTE = 1, SE = 1), Excellence ($0.9 \leq$ PTE < 1, $0.75 \leq$ SE < 1), Scale Efficiency Improvement ($0.9 \leq$ PTE < 1, $0 \leq$ SE < 0.75), Pure Technical Efficiency Improvement ($0 \leq$ PTE < 0.9, $0.75 \leq$ SE ≤ 1), Lag($0 \leq$ PTE < 0.9, $0 \leq$ SE < 0.75). By this standard, this paper classifies the sample companies in 2017 and 2018, as listed in Tables 8 and 9.

Table 8. Classification of enterprise innovation type in 2017.

Type of Innovation	Stock Abbreviation
Pioneer (total of 12)	Teamax, Lianluo Interactive, Gci Sciand Tech, Jieshun Science and Technology, Sinodata, Lanxum, Egova, Infogem, DVX, Tianze Info, CNCR-IT, Nari
Excellence (total of 14)	Shiji Information, Sinonet, Taiji, CTFO, SUNA, Das Intellitech, Dingli Communications, Gosun, Century Real, AVIT, Bluedon, Watertek Information, PCI-Suntek Technology, East-China Computer
Scale Efficiency Improvement (total of 3)	Iflytek, Wangsu Sci and Tech, Neusoft
Pure Technical Efficiency Improvement (total of 49)	Digital China Information, Dongfang Electronics, Newland, YGsoft, Montnets Group, Bewinner Tech, Qiming Information, Wisesoft, Talkweb Information, Westone, Ligong Environment, Wantong Technology, SCIYON, COSCO SHIP TECH, NavInfo, Glodon, Rongji Software, Century Huatong, Beyondsoft, Enjoyor, Supermap Software, Tianyuan Dic, Wonders Information, Eastsoft, Meiya Pico, E-hualu, TRS, Thunisoft, Massci, Philisense, Bringspring, Fuchun Technology, Toyou Feiji, Surfilter, Boomsense Technology, Huahongjt, Hoperun Software, Goldcard Smart, VRV Software, Teamsun, Hundsun, Sunyard, INESA Intelligent, Inspur Software, Baosight, Insigma, Sunwin, Avcon, Great Wisdom

Comparing the classifications of Tables 8 and 9, " Pioneer" companies are double year-on-year in 2018, and the total number reaches twenty-four, accounting for 30% of the sample companies. "Excellence" companies have declined while "Scale Efficiency Improvement" and "Lag" remains constant. Simultaneously, "Pure Technical Efficiency Improvement" is still the main representative type of enterprise innovation (forty-nine and forty-five in 2017 and 2018, accounting for 61.25% and 56.25%), which is mutually confirmed with the previous analysis in stage one.

Table 9. Classification of enterprise innovation type in 2018.

Type of Innovation	Stock Abbreviation
Pioneer (total of 12)	Teamax, Montnets Group, Wisesoft, Lianluo Interactive, Sinonet, Wantong Technology, CTFO, Rongji Software, Jieshun Science and Technology, Sinodata, Lanxum, Enjoyor, Century Real, Tianze Info, E-hualu, Thunisoft, Bluedon, Watertek Information, Nari, China National Software, Yonyou Network, INESA Intelligent, Neusoft, East-China Computer
Excellence (total of 6)	Dingli Communications, Egova, Infogem, Fuchun Technology, PCI-Suntek Technology, Great Wisdom
Scale Efficiency Improvement (total of 3)	Newland, Iflytek, Wangsu Sci and Tech
Pure Technical Efficiency Improvement (total of 45)	Digital China Information, Dongfang Electronics, YGsoft, Bewinner Tech, Shiji Information, Qiming Information, Talkweb Information, Westone, Ligong Environment, Taiji, SCIYON, COSCO SHIP TECH, NavInfo, SUNA, Das Intellitech, Gci Sciand Tech, Century Huatong, Beyondsoft, Supermap Software, Tianyuan Dic, Avcon, Gosun, DVX, Sunwin, Wonders Information, Eastsoft, Meiya Pico, TRS, CNCR-IT, AVIT, Massci, Philisense, Bringspring, Toyou Feiji, Surfilter, Boomsense Technology, Huahongjt, Goldcard Smart, VRV Software, Teamsun, Hundsun, Sunyard, Inspur Software, Insigma
Lag (total of 2)	Glodon, Baosight

In geographical distribution, seventy-one companies are located in Eastern China, five companies in Central China, and four companies in Western China. The overall innovation situation in Eastern China is better than regions of Central and Western China. Simultaneously, there are a large number of "Pioneer" and "Excellence" companies including Lianluo Interaction, Jieshun Science and Technology, Sinodata, etc., but at the same time, there are certain differences. There are "Lag" companies, such as China National Software and Yonyou Network in 2017, and Glodon and Baosight in 2018, which are all located within Eastern China, concentrated in Beijing and Shanghai. Iflytek located in Central China has not taken off the scale efficiency improvement hat within two years. Qiming Information and Talkweb Information are still "Pure Technical Efficiency Improvement" companies; both Sinonet ("Excellence") and Wantong Technology ("Pure Technical Efficiency Improvement") are becoming "Pioneer" companies. Western China is represented by Sichuan, Chongqing, and Guangxi. Teamax of Guangxi Province has maintained the momentum of innovation pioneer in the past two years, followed by Sichuan Wisesoft from types of "Pure Technical Efficiency Improvement" to "Pioneer", while both Westone (Sichuan) and Massic (Chongqing) are in the ranks of "Pure Technical Efficiency Improvement".

The regional distribution characteristics of efficiency and the differences in efficiency of enterprises are mainly caused by the imbalance of regional development. The economy of Eastern China is more developed than that of other regions. Economic development in the eastern regions is also better than that in the west. In recent years, the western regions have also been developing continuously, such as Sichuan, Chongqing, and Guangxi. Innovative intellectuals and resources always flow to developed regions and cities, and the information technology enterprises are more efficient than those in other regions.

4. Conclusions and Policy Recommendations

4.1. Conclusions

(1) The environmental variables indeed influence the enterprise innovation efficiency of software and information technology services. At the micro aspects, firstly, the longer the establishment of the enterprise, the higher the personnel quality and the utilization rate of productive capital such as research and development equipment. Secondly, expanding

market share may result in some short-term investment redundancy. Finally, most enterprises have a relatively high scale efficiency; the rapid expansion of enterprise scale will result in the wasted resources of various investment innovations. At the macro aspects, firstly, regions with more economic development have greater advantages for obtaining innovation resources, but also polarization exists where high-density innovation resources are not fully utilized, inevitably causing some companies to have low efficiency. Secondly, the opening level to the outside world of the province where enterprise is located has different effects on enterprise innovation. If enterprises rely excessively on technology introduction and purchase, a shift in focus is likely to occur when companies pay more attention to production activities than innovation activities. Finally, government subsidies and financial development will help enterprise improve innovation efficiency, and it is necessary to expand the support scale appropriately.

(2) The overall enterprise innovation efficiency of software and information technology services is not high. Empirical results show that enterprises are subject to the comprehensive constraints of scale efficiency and pure technical efficiency, but the problems of most companies focus on pure technical efficiency. There is an extremely low enterprise innovation efficiency and a significant difference in decomposition values (TE, PTE, and SE) without considering the influence of environmental factors and random interference. After eliminating the influence of external environments, enterprise's innovation efficiency has improved significantly, but scale efficiency is still the highest efficiency value in general; therefore, pure technical efficiency improvement is the main representative type of enterprise innovation.

(3) After eliminating the influences of external environment and random errors, the scale returns of software and information technology services enterprises tend to be increasing and this shows that the enterprise's innovation scale has not yet reached the best level. In 2017, before adjustment, the number of companies with increasing, decreasing, and constant scale returns is sixteen, fifty, and fourteen, respectively, but after adjustment, it became thirty, thirty-five, and fifteen. In 2018, before adjustment the number of companies with increasing, decreasing, and constant scale returns is five, forty-four, and thirty-one, and after adjustment, it became thirty-two, twenty, and twenty-eight. The actual scale returns reflect how there is still a certain difference between the current scale and the optimal scale, so enterprises should continue to increase innovation investment to narrow this gap while trying to achieve the optimal innovation scale.

(4) Enterprise innovation of the software and information technology services industry has a regional gap. Eastern China is a gathering place for "Pioneer" and "Excellence" innovation, surpassing Central and Western China in number and polarizing in innovation quality. On the contrary, Central and Western China are prominently expressed in quality rather than number, and the effect of industrial clusters is not as good as the developed regions in Eastern China.

4.2. Policy Recommendations

In view of the results of the above empirical analysis, for further improving the enterprise innovation efficiency of the software and information technology service industry, several measures could be taken based on macro and micro aspects.

From macro aspects, government should increase enterprise innovation subsidies, speeding up a sound mechanism for talent training and talent introduction, especially in Central and Western China. In addition, it is also necessary to accelerate the expansion of financial institutions in various regions and to increase the size of corporate loan balances. While increasing the openness level to the world, government should give more attention to enterprise's own management and technical exchanges and should avoid having an over-reliance on technology introduction, aiming instead to ultimately have an independent R&D system.

From micro aspects, different enterprises should adopt different measures to improve innovation efficiency. For "Pioneer" companies, PTE and SE have reached the maximum, so these companies should continue to maintain the current R&D state and production scale, and steadily march into greater R&D ability in high-quality products or services, core technologies, and key areas. For "Excellence" companies, PTE and SE are basically around 0.9, and the improvement room is not large. After optimizing the allocation of current innovation investment resources, strengthening rational enterprise management and mild scale adjustment, they can quickly become "Pioneer" companies. For "Scale Efficiency Improvement" companies, their PTE is higher, and some have even reached the efficiency frontier, but the SE is low. The main factor restricting the improvement of enterprise innovation efficiency is scale efficiency. Therefore, it is necessary to expand the enterprise R&D scale to reach the scale level that matches the innovation investment. For "Pure Technical Efficiency Improvement" companies, the SE is higher, but the PTE is lower, so the improvement direction concerns how to improve the pure technology efficiency. Enterprises should absorb advanced management concepts and strengthen and improve internal management systems, simultaneously, while making overall plans for allocation and various forms of innovative resource usage to reduce resource waste. For "Lag" companies, both PTE and SE have "double low" situations, which together leads to a situation where the innovation efficiency lags behind other enterprises. Therefore, in addition to improving the internal management level and optimizing the allocation of innovative resources, it is also necessary to gradually expand the R&D scale.

4.3. Research Outlook

Some shortcomings exist in this paper. On the one hand, due to the lack and incompleteness of relevant statistical data, many periods' data is not available for research and the efficiency change over a longer period cannot be reflected. At the same time, the indicators used in this study have yet to be further verified. On the other hand, the company's main business has not been subdivided into the industry's fields, and thus the innovation efficiency differences in various fields cannot be measured. With the further improvement and accuracy of statistical index data, the research on innovation efficiency will be carried out in a larger space and for a longer period, the overview of enterprise innovation will be more comprehensive and accurate, and the recommendations will be more targeted.

4.4. Research Limitations

There are some shortcomings in the research of enterprise innovation efficiency in this paper. On the one hand, there are relatively few statistics on software and information technology services enterprises. Not only is there a lack of major indicators, but there is also a big difference in data integrity between eastern, central, and western regions. Therefore, there are not many periods available for study, which cannot reflect efficiency changes over a longer period. At the same time, the indicators used in this study need to be further verified, especially some environmental variables. In this paper, a comprehensive selection of environmental variables is made by considering the research results of many scholars. On the other hand, according to the scope of the enterprise's main business, it is not possible to subdivide the enterprise's business in the industry field. Therefore, it is impossible to measure the differences in innovation efficiency between different fields.

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