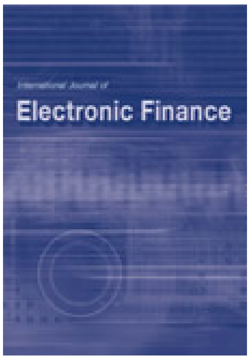

International Journal of Electronic Finance

ISSN online: 1746-0077 - ISSN print: 1746-0069
https://www.inderscience.com/ijef

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DOI: 10.1504/IJEF.2024.10057607

Article History:

Received:	07 August 2022
Last revised:	01 April 2023
Accepted:	28 April 2023
Published online:	11 December 2024

Research on the operational efficiency of Chinese fintech companies based on the DEA model

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Abstract: Fintech is important for China's 'new infrastructure' and for driving strategic innovation at the national level. Measurement systems are constructed considering cost income and company development. The DEA model is used to analyse the operating efficiency and slack variables of 55 listed fintech companies from 2014 to 2019. This paper distinguishes between the establishment years, enterprise attributes, and scale of companies. It concludes that companies with high establishment years are more efficient than those with low establishment years. The average comprehensive technical efficiency changes of non-state-owned enterprises are slightly higher than those with low establishment years. Non-SBM effective enterprises' investment redundancy indicators are total assets, payable employee compensation, and the number of employees, while insufficient output is reflected in net profit's indicator. Based on the research results, suggestions are made to promote the sustainable development of fintech in China, which is significant for the promotion of financial innovation in China.

Keywords: fintech; corporate operational efficiency; standard DEA model; dynamic DEA model; SBM-DEA model; slack variables; decision-making unit; DMU; establishment years; enterprise attributes; scale of companies.

Reference to this paper should be made as follows: Song, X., Peng, P. and Qin, X. (2025) 'Research on the operational efficiency of Chinese fintech companies based on the DEA model', *Int. J. Electronic Finance*, Vol. 14, No. 1, pp.22–41.

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1 Introduction

In recent years, financial technology has been widely used in risk management, supply chain finance, payment settlement, and other fields. As an important part of China's 'new infrastructure', financial technology can improve the efficiency of financial services while reducing operating costs, thereby promoting strategic innovation at the enterprise and even national level. Influenced by the central government's policy, various regions have also actively introduced relevant policies to support the development of the local fintech industry. Since 2018, Beijing, Shanghai, Guangzhou, Shenzhen, Chongqing, Chengdu, and other cities have successively introduced a series of policies, such as actively applying for fintech pilot projects and introducing effective supporting measures, committing to talent subsidies, financing incentives, and other preferential policies to attract high-quality financial technology companies and talents and promote the development of the financial technology industry. In the global capital market, the fintech industry continues to be favoured, and the investment volume and transaction scale are also gradually increasing. Overall, North America and Asia lead the rest of the world.

Based on the development background of the financial technology industry and China's strategic position, it is of great significance to explore the operational efficiency of the current financial technology enterprises, evaluate the development status and prospects of the financial technology industry objectively, and analyse the ways to improve efficiency accordingly to promote the development of China's fintech industry.

2 Literature review

When the academic community studies financial technology issues, it chiefly focuses on the impact of financial technology on the profitability, operational efficiency, and risk control of various entities (financial institutions and non-financial institutions) (Li and Shen, 2019; Tian et al., 2020; Zhang et al., 2020a). After further refining the research field to fintech companies, the research mainly focuses on fintech companies from the aspects of company value judgment and business model (Ge et al., 2017; Liu, 2019). Given that there is limited literature on the operational efficiency of fintech companies at present, this paper mainly reviews various evaluation methods for studying the operational efficiency of companies.

At present, the various efficiency problems of companies have primarily been studied through stochastic frontier analysis (SFA) and data envelope analysis (DEA). The DEA measurement method is often used in the efficiency evaluation of public utilities. Mitropoulos et al. (2013) used a two-stage DEA model to evaluate 96 general hospitals in the Greek national health system. DEA can also provide identification references and possible adjustment options for inefficient enterprises or industries to promote their efficiency improvements. Barros et al. (2012) used a two-stage DEA to evaluate the technical efficiency of French regional airports from 2000 to 2008. The results showed that the technical efficiency of French airports is uneven; therefore, substantial scope remained for improvement in technical efficiency. In the integration and extension of the DEA model, Kantor and Maital (1999) used the data of a large Middle Eastern bank with 250 branches to establish a measure of bank branches based on the cost of activity accounting (ABC) and DEA models. An approach to agency-specific product efficiency and the resulting activity-based management approach provide managers with detailed quantitative performance benchmarks against their company or department-specific business activities. Chinese scholars usually take the DEA model results as their judgment basis for evaluating enterprise operation efficiency. Zhang et al. (2020b) used the Charnes, Cooper and Rhodes (CCR) model in the DEA model to analyse the operational efficiency of China's 'unicorn' enterprises and concluded that listed companies investing in 'unicorn' enterprises have higher operational efficiency. Yang et al. (2022) used a two-stage DEA model to study the evaluation of scientific research performance in universities. The results of the study effectively reflected the internal factors that made scientific research performance poor so as to provide directions for the improvement of system efficiency.

Recently, a three-stage DEA model combining the above two research methods has also emerged. In the first stage, the standard DEA model is used to judge operational efficiency; the second stage uses the SFA model to eliminate the interference of environmental variables; and in the third stage, new adjusted input data is used to obtain the efficiency values of each decision-making unit (DMU). Based on the data of eight Turkish coal enterprises, Kasap et al. (2007) used the three-stage DEA model to conclude that the average efficiency value in this industry increased from 87.5% to 92.3%. Standard DEA is commonly used in efficiency analysis and has wide applicability (Golany and Roll, 1993).

The DEA model has been developing continuously in recent years and has gradually helped derive the developed DEA, dynamic DEA (DEA-Malmquist), inverse DEA, and SBM-DEA models. The DEA-Malmquist model can analyse panel data; hence, it has wider applicability. Zhang (2020) used the Banker, Charnes and Cooper (BCC) model to conduct a static analysis of 23 agricultural and animal husbandry listed companies in 2019 to judge the operational efficiency of Chinese agriculture and animal husbandry enterprises and evaluated the changes of sample data from 2013 to 2019 by using Malmquist index method. The study found that the operating efficiency of these enterprises had a large gap, and technical efficiency was the main reason for the ineffective operation efficiency of some enterprises. Gong and Jing (2019) also constructed the DEA-Malmquist model and concluded that the overall change in logistics efficiency in the six central provinces still needs to be improved, and the efficiency change between provinces is quite different. In recent years, some scholars have also used the non-radial SBM-DEA model to measure the efficiency of enterprise operations. Yan and Jiang (2019) used this model to measure the efficiency of listed companies in China's cultural service industry. In addition, some scholars also use the DEA model to analyse the innovation efficiency of enterprises (Dou et al., 2020; Guo et al., 2020; Meng and Xu, 2021), financing efficiency (Huang, 2020), capital utilisation efficiency (Chen and Wei, 2019), and investment efficiency (Xiong and Liu, 2020).

Compared with DEA, SFA needs to estimate the production function on the basis of the set production function, which is a parametric method. DEA does not set a specific function form; it first finds a DMU with an efficiency of 1 on the production boundary through linear programming and then uses the ratio of the productivity of the remaining DMUs to the productivity of the DMU on the production boundary as the DMU. An indicator of technical efficiency, DEA is, therefore, a non-parametric method. The DEA model mainly has four advantages. First, the DEA model is friendly to DMUs with multiple inputs and outputs when measuring their operational efficiency. When using the DEA model, the measurer does not need to pre-set the form of the production function, which is of great convenience to the user. Second, it is not affected by input-output data units, and the DEA model can calculate both numerical and proportional data. Third, the weights of DEA indicators generated by mathematical programming are not easily affected by subjective factors, and the accuracy is high. Finally, the DEA model can compare and analyse the efficiency value and slack variables, helping users further understand the input and output usage of each DMU. Compared with DEA, SFA considers the influence of the existence of random errors on the results, but the model must determine the production function form in advance and can only analyse the situation of a single output. Considering the advantages of the DEA model and its characteristic of more expansion types, it can evaluate and analyse the operation efficiency of enterprises from multiple perspectives. Therefore, the DEA model was selected in this study to analyse the operational efficiency of fintech companies and further uses the dynamic DEA (DEA-Malmquist Index) model as well as the SBM-DEA model for refinement and in-depth analysis of the data.

At present, there are 56 listed companies in China's fintech sector. As industry representatives in the fintech sector, they have a relatively large benchmark. After removing the company 'Northking' due to incomplete data, this study provides the management and investors of fintech companies with a basis for evaluating operational efficiency.

Compared with the existing literature, the novelty of this study is mainly reflected in four points. First, there is currently a lack of research on the operational efficiency of fintech listed companies in the academic world. This study closely follows the current hot spots of financial innovation and financial development prospects and further broadens the research depth of financial technology research. Second, research using the DEA model to analyse industry efficiency has not yet been applied in the field of financial technology. This study broadens the application scope of DEA model analysis. Third, to further enhance the universality of the model and to ensure the accuracy of the index construction when constructing the operational indicators of financial technology companies, this study constructs two sets of measurement systems from the perspective of cost income and company development, respectively. After comparing and analysing the empirical results, it also verifies the robustness of the measurement method and test results. Finally, this study further distinguishes the establishment years, enterprise attributes, and enterprise scale of fintech enterprises and concludes that the overall operation efficiency of enterprises with long establishment years is higher than that of enterprises with short establishment years, and the average comprehensive technical efficiency change value of non-state-owned enterprises is overall slightly higher than that of state-owned enterprises. Additionally, the operation efficiency of large enterprises is generally higher than that of small and medium-sized enterprises, which further enriches the research results of the operation efficiency evaluation of financial technology enterprises.

3 Principles of the DEA model

3.1 Principle of standard DEA model

DEA is a non-parametric test method first proposed in 1978 by Charnes et al. (1978). In this model, the evaluated unit is called the DMU. The model constructs a data envelope curve by choosing numerous input and output data of the DMU and using the method of linear programming in mathematics. Among them, the effective point of DEA will fall on the leading edge, and the efficiency value is 1; the invalid point is a relative efficiency value between 0 and 1, which will fall on the leading edge.

3.1.1 CCR model

The CCR model in the DEA model is primarily used to calculate the resource allocation efficiency of DMUs with constant returns to scale. The objective function is the efficiency maximisation index of the j_0^{th} DMU. By constraining the efficiency of all DMUs, the below model is obtained:

$$\max h_{j_0} = \frac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{r=1}^{m} v_i x_{ij_0}}$$

$$s.t. \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{r=1}^{m} v_i x_{ij}} \le 1,\ j = 1, 2, ..., n$$

$$u \ge 0, v \ge 0$$

x_{ij_0} represents the total amount of j_0^{th} DMU to the input factor in I, and y_{rj_0} represents the total output of the r^{th} product in the j_0^{th} DMU. v_i represents the proportion of the i^{th}

type of input to the total input, and u_r represents the proportion of the r^{th} type of output to the total output.

Let $w = \frac{1}{v^T x_0} v$, $\mu = \frac{1}{v^T x_0} u$ after the Charnes-Cooper transformation. It can be transformed into the following linear programming model:

$$\max h_{j_0} = \mu^T y_0$$

$$s.t. \begin{cases} w^T x_j - \mu^T y_j \ge 0, \ j = 1, 2, ..., n \\ w^T x_0 = 1 \\ w \ge 0, \mu \ge 0 \end{cases}$$

After introducing slack variables S^+ and residual variables S^{-1}, the inequality constraints are transformed into equality constraints, and the model can be simplified as follows:

$$\min \theta$$

$$s.t. \begin{cases} \sum_{j=1}^{n} \lambda_j y_j + S^+ = \theta x_0 \\ \sum_{j=1}^{n} \lambda_j y_j - S^- = \theta y_0 \\ S^+ \ge 0, S^- \ge 0 \\ \lambda_j \ge 0, \ j = 1, 2, ..., n \end{cases}$$

1 If $\theta^* = 1$, $S^+ = 0$ and $S^- = 0$, then the DMU is DEA-valid, and it is technically valid and scale-valid at the same time.

2 If the $\theta^* = 1$ condition is met, but $S^+ = 0$, $S^- = 0$ are not met, then the DMU is weak DEA-valid and not both technically valid and scale valid.

3 If $\theta^* < 1$, then the DMU is not DEA-effective, and neither the technology nor the scale is effective.

3.1.2 BCC model

The previously proposed CCR model is obtained under the premise of constant returns to scale, but in practice, the returns to scale of technological innovation are not fixed. Banker et al. (1984) expanded DEA analysis on fixed economies of scale in 1984. Furthermore, a BCC model considering variable return to scale (VRS) is proposed. The BCC model needs to increase the convexity assumption to satisfy the condition of variable returns to scale.

In the simplified single-input single-output background, the frontier surface of the CCR model is a ray passing through the origin, while the frontier surface of the BCC model is the curve containing all of the outermost DMUs. Usually, DEA analysis of CCR and BCC models can be used to assess the scale efficiency (SE) of a DMU. Considering that the BCC model is more general, the standard DEA analysis part of the empirical portion of this study uses the BCC model.

3.2 The principle of the dynamic DEA (DEA-Malmquist Index) model

The CCR and BCC models in the standard DEA model cannot measure changes in productivity across time periods, but the DEA-Malmquist model compensates for this deficiency, so it has wider applicability to panel data.

The Malmquist model uses the distance function (E) to calculate the change value of total factor productivity under the MPI_I^t condition of period t, and similarly, MPI_I^{t+1} expresses the change value of total factor productivity under the condition of period $t + 1$. The mathematical expressions of the two are as follows:

$$\text{MPI}_I^t = \frac{\text{E}_I^t\left(x^{t+1}, y^{t+1}\right)}{\text{E}_I^t\left(x^t, y^t\right)} \text{ and } \text{MPI}_I^{t+1} = \frac{\text{E}_I^{t+1}\left(x^{t+1}, y^{t+1}\right)}{\text{E}_I^{t+1}\left(x^t, y^t\right)}$$

To consider the technical levels of both periods, their geometric mean is taken. The productivity index can be represented by the product of the technical progress change index (EFFCH) and comprehensive technical efficiency change index (TECHCH). In addition, the comprehensive technical efficiency change index can be expressed as the product of the scale efficiency change index (SECH) and pure technical efficiency change index (PECH).

3.3 Principle of non-radial SBM-DEA model

When considering the problem of slack variables, the standard DEA model only considers the proportional changes (radial changes) of the input and output of each DMU but does not fully consider the slack changes of each DMU itself. Hence, Tone (2001) proposed the Slacks-Based Measure (SBM)-DEA model, which solved the drawbacks brought by radial measurement.

If n represents the number of DMUs, then each DMU has its own input vector $x \in R^p$ and output vector $y \in R^q$, so the input matrix of n DMU is $X = [x_1, x_2, \ldots, x_n] \in R^{p*n}$, and the output matrix is $Y = [y_1, y_2, \ldots, y_n] \in R^{q*n}$ ($X > 0$ and $Y > 0$). Under the condition of constant returns to scale, the possible sets of production are $P = \{(x, y)|\ x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0\}$, $\lambda \in R^n$, and the input and output ineffective ratios in the SBM model are $\frac{1}{p}\sum_{i=1}^{p} s_i^- / x_{io}$ and $\frac{1}{q}\sum_{r=1}^{q} s_r^+ / y_{io}$, respectively. By reducing input or increasing output, enterprises can be promoted to achieve an SBM-efficient state. Because the SBM-DEA model used in this study is an input-oriented DEA model with variable returns to scale, a convexity condition needs to be added, and the expression for it is as follows:

$$\min \rho = \frac{1 - \frac{1}{p}\sum_{i=1}^{p} s_i^- / x_{io}}{1 + \frac{1}{q}\sum_{r=1}^{q} s_i^+ / y_{io}}$$

$$s.t.\begin{cases} x_0 = X\lambda + s^- \\ y_0 \le Y\lambda \\ \lambda \ge 0, s^- \ge 0 \\ \sum \lambda_j = 1,\ j = 1, 2, ..., n \end{cases}$$

ρ is the final efficiency evaluation value, and $\lambda = (\lambda_1, \lambda_2, \cdots, \lambda_n)^T$ is the weight vector. x_{io} is i^{th} item in DMU_0 input vector x_o, and y_{ro} is r^{th} item in DMU_0 output vector y_o. Similarly, s_i^- is the input relaxation quantity s^- item. When $\rho = 1$ (i.e., $s^- = s^+ = 0$), the evaluated DMU_0 is SBM effective; otherwise, the evaluated DMU_0 is ineffective, there is insufficient output or redundant input, and the input and output can be improved in a targeted manner.

4 Model construction

Enterprise operation efficiency refers to the ability of the enterprise to use the assets under its control to generate economic benefits, that is, the best state of input-output or cost-benefit ratio. The higher the operation efficiency is, the stronger the ability of the company to create value by using existing resources, and the more attention and investment it is conducive to attract.

4.1 Sources of data collection

This study selects the financial data of 55 listed companies in China's fintech sector from 2014 to 2019 as the research object, and the data are derived from the financial reports those companies disclose. Of the 55 fintech companies selected, 32 were established more than 20 years ago, while the remaining 23 were established less than 20 years ago. From the perspective of enterprise attributes, the number of state-owned enterprises (including central and local governments) is relatively small, with only 10% and 18% of the total, respectively. In terms of enterprise scale, there are 48 large and medium-sized companies, accounting for 87% of the total companies, compared to the seven small and medium-sized enterprises. From the perspective of their administrative regions, they are mainly distributed in the eastern region.

4.2 Common indicators of the company's operational efficiency system

In recent years, most of the literature selects the company's operational efficiency indicators from the perspective of cost and revenue. Referring to Xu and Yang (2014) and Yan and Jiang (2019) in selecting the principles of input and output indicators, it can be seen that when selecting efficiency indicators from the perspective of cost and income, the input indicators mainly include main business cost, total assets, number of employees, fixed assets, employee compensation payable, and operating expenses. The output indicators primarily include main business income, net profit, cash paid to employees, and investment income. Zhang et al. (2020b) innovatively used financial indicators to construct input indicators and output indicators of the company's operational efficiency from the perspective of company development, focusing on the operating model (total assets), operating capabilities (total asset turnover, fixed assets, turnover ratio), and operational risk control (current ratio, quick ratio) and selected the return on equity and profit margin of main business as the operational efficiency output indicators of listed companies to reflect the company's main business, operating capacity, and profitability.

Table 1 Comparison of enterprise operation efficiency indicators from the perspective of cost and income and the perspective of company development

	Cost-income perspective			*Company development angle*		
	Variable symbol	*Indicator name*	*Indicator description*	*Variable symbol*	*Indicator name*	*Indicator description*
Input indicator	Asset	Total assets (100 million yuan)	The amount of capital of fintech companies	Total assets turnover ratio (TATR)	Total asset turnover	Fintech companies' utilisation efficiency of various assets and overall operating conditions
	Wage	Payroll payable (100 million yuan)	Labour costs	Liquidity ratio (LR)	Current ratio	Short-term solvency of the firm
	Cost	Operating cost (100 million yuan)	Upfront investment in operations	Debt to assets ratio (DTAR)	Assets and liabilities	Long-term solvency of the company
	Staff	Number of employees (10,000 people)	The human input of fintech companies			
Output indicator	Income	Operating income (100 million yuan)	Reflects the business capabilities of the company	ROE	ROE	Corporate profitability
	Profit	Net profit (normalised)	Corporate profitability			

4.3 Determination of input and output indicators in this study

Comprehensively considering the research results in the existing literature, this study mainly selects the company's operational efficiency indicators from the perspective of cost and income. However, considering that the indicators constructed from the perspective of cost and incomes are absolute values, they may be affected by factors such as the size of the company and the company's establishment years. To ensure the robustness of the results, this study also constructs another company operation efficiency evaluation system in terms of company development and compares the two results in the basic model stage to draw general conclusions. From the perspective of cost and income, because the financial technology industry is a technology-and talent-oriented industry, indicators related to assets and manpower should be included. In this study, total assets, employee compensation payable, operating costs, and the number of employees are used as the input indicators, and the operating income and net profit are selected as the output indicators. Because the DEA model requires that the input and output must be positive numbers, considering that the net profit may have a negative value, this study normalises the net profit indicator. The processing formula is as follows:

$$y = \frac{y_{ij} - \min(y_{ij})}{\max(y_{ij}) - \min(y_{ij})} * 0.9 + 0.1$$

$$y_{ij} \in y_j = (y_{1j}, y_{2j}, \ldots, y_{sj})^T, \; j = 1, \ldots, n$$

From the perspective of company development, this study primarily draws on the index construction method of Zhang et al. (2020b) and uses the company's financial ratio indicators to form a set of evaluation systems. The input indicators are total asset turnover ratio, current ratio, and asset-liability ratio, and the output indicator is the return on net assets. The comparison of enterprise operation efficiency indicators from the perspective of cost and income and the perspective of company development is shown in Table 1.

5 Results and discussion

5.1 Analysis of overall operational efficiency (BCC model)

This study used the DEAP2.1 software to conduct basic calculation of the company's operational efficiency. To ensure the relative accuracy of the results, the calculation results of the operational efficiency indicators from the perspective of the company's development are compared with the results of the operational efficiency indicators from the perspective[2] of cost and income. It can be seen from Table 2 that no matter which index system is used, it shows that the comprehensive efficiency value of the six companies, namely HengBao, Julong, SINOSUN, Tianli Technology, Tansun Technology, and Fortune Trend Tech, is 1. The companies with valid DEA account for 11% of the sample, while the other companies are not valid for DEA. Overall, Chinese fintech companies are operating less efficiently. In addition, the average values of the two index systems are 0.879 and 0.867, respectively, and the difference is not large. Therefore, in general, the overall comprehensive efficiency value of fintech listed companies is 0.87, and the pure technical efficiency and scale efficiency values are about 0.9 each. The overall operating efficiency needs to be further improved.

5.2 Analysis of dynamic operational efficiency (DEA-Malmquist model)

Further, the DEA-Malmquist index method is used to calculate the change value of comprehensive technical efficiency, technological progress, pure technical efficiency, scale efficiency, and TFP (total factor productivity change index) of the 55 companies. The calculation results are shown in Table 3.

Table 2 Input-based BCC-DEA model results

Company	*Results of operational efficiency indicators from a cost-revenue perspective*				*Operational efficiency indicator results from a company development perspective*			
	Overall efficiency value	*Pure technical efficiency value*	*Scale efficiency value*	*Returns to scale*	*Overall efficiency value*	*Pure technical efficiency value*	*Scale efficiency value*	*Returns to scale*
China Information	0.940	0.989	0.950	drs	0.654	0.822	0.796	irs
ZJBC Information	0.836	0.854	0.979	drs	1.000	1.000	1.000	-
Nantian Information	0.775	0.810	0.956	drs	0.756	0.819	0.922	irs
Inspur	0.997	1.000	0.997	drs	0.634	0.925	0.686	irs
Newland	0.845	0.877	0.963	drs	0.858	0.873	0.983	irs
Eastcompeace Technology	0.826	0.826	0.999	irs	0.680	0.720	0.944	irs
DHC Software	0.971	1.000	0.971	drs	0.956	0.963	0.993	irs
HengBao	1.000	1.000	1.000	-	1.000	1.000	1.000	-
GRG Banking Equipment	0.690	1.000	0.690	drs	0.895	0.904	0.990	drs
Guangzhou Kingteller Technology	1.000	1.000	1.000	-	0.985	0.995	0.990	irs
2345 Network	0.528	0.617	0.855	drs	1.000	1.000	1.000	-
SZZT Electronics	0.758	0.759	0.999	drs	0.842	0.867	0.972	irs
Westone	0.944	0.954	0.990	drs	0.764	0.767	0.996	drs
Asia Link Technology	1.000	1.000	1.000	-	0.932	0.983	0.948	irs
Taiji Computer	0.910	0.966	0.942	drs	0.675	0.887	0.761	irs
Glodon	1.000	1.000	1.000	-	0.996	1.000	0.996	drs
Venustech	0.835	0.835	1.000	-	0.913	0.920	0.993	irs
Great Chinasoft Technology	0.734	0.735	0.999	drs	0.961	1.000	0.961	irs

Table 3 DEA-Malmquist exponential model results

Company	*Results of operational efficiency indicators from a cost-revenue perspective*					*Operational efficiency indicator results from a company development perspective*				
	Comprehensive technical efficiency change value	*Technological progress change value*	*Pure technical efficiency change*	*Scale efficiency change value*	*TFP*	*Comprehensive technical efficiency change value*	*Technological progress change value*	*Pure technical efficiency change*	*Scale efficiency change value*	*TFP*
China Information	0.970	1.018	0.969	1.001	0.987	1.027	0.986	1.003	1.024	1.012
ZJBC Information	0.995	0.984	0.991	1.004	0.979	0.889	0.998	0.990	0.898	0.887
Nantian Information	1.030	0.982	1.021	1.009	1.011	0.979	1.003	0.989	0.991	0.982
Inspur	1.001	1.015	1.000	1.001	1.015	1.013	0.960	0.944	1.073	0.973
Newland	0.988	0.975	0.997	0.991	0.964	0.995	1.023	1.003	0.991	1.017
Eastcompeace Technology	0.972	0.996	0.972	1.000	0.968	1.027	0.982	1.035	0.992	1.008
DHC Software	1.006	0.956	1.000	1.006	0.962	0.951	1.019	0.972	0.978	0.968
HengBao	1.000	0.917	1.000	1.000	0.917	0.958	1.028	0.973	0.985	0.986
GRG Banking Equipment	0.998	0.973	0.949	1.051	0.970	1.007	1.009	1.018	0.989	1.016
Guangzhou Kingteller Technology	1.000	0.990	1.000	1.000	0.990	1.003	1.105	1.001	1.002	1.108
2345 Network	1.136	1.117	1.101	1.032	1.270	0.982	0.980	0.990	0.991	0.962
SZZT Electronics	1.007	0.977	1.008	0.999	0.984	0.977	1.086	0.983	0.993	1.061
Westone	0.978	0.952	0.976	1.002	0.931	1.046	0.974	1.054	0.992	1.020
Asia Link Technology	1.000	0.960	1.000	1.000	0.960	0.989	0.980	1.003	0.986	0.969
Taiji Computer	1.009	0.974	0.998	1.011	0.983	1.026	0.985	0.976	1.052	1.011
Glodon	1.000	0.987	1.000	1.000	0.987	0.987	1.016	0.995	0.992	1.003
Venustech	1.006	0.976	1.006	1.000	0.982	0.971	0.981	0.973	0.999	0.953
Great Chinasoft Technology	1.064	0.965	1.064	1.000	1.026	0.856	1.003	0.935	0.916	0.859
China Information	1.011	1.030	1.004	1.007	1.042	0.903	0.979	0.999	0.904	0.884

Table 4 Empirical results for distinguishing years of establishment, enterprise attributes, and enterprise scale

	Comprehensive technical efficiency change value	*Technological progress change value*	*Pure technical efficiency change*	*Scale efficiency change value*	*TFP*	*Company abbreviation*	*Comprehensive technical efficiency change value*	*Technological progress change value*	*Pure technical efficiency change*	*Scale efficiency change value*	*TFP*
20 years ≥ average value	0.999	0.958	0.995	1.003	0.956	Age < 20 years average value	0.999	0.939	1.002	0.997	0.937
Non-state-owned enterprise average value	1.000	0.950	1.004	0.996	0.950	State-owned enterprise average value	0.998	0.951	0.998	1.000	0.940
Large enterprise average value	1.004	0.948	1.002	1.002	0.952	SME average value	0.991	0.938	0.992	0.999	0.929

From Table 3, the results of the indicators from the perspective of cost and income show that the average value of changes in comprehensive technical efficiency is 1; that is, the efficiency level remains stable. The results of indicators from the perspective of company development show a similar average value of 0.99. The results of the cost-income perspective index reveal that the comprehensive technical efficiency change of 34 companies is greater than or equal to 1, which indicates that 62% of the listed fintech companies have shown a trend of technological progress. It also shows that there are 26 enterprises whose efficiency change value is greater than or equal to 1. From the perspective of technological progress change, the index result of the company's development perspective is 1.007, which indicates that the technological innovation capability of listed fintech companies has been continuously improved. However, regardless of which index system is used, the final total factor productivity index is less than 1, which indicates that the overall operating efficiency of enterprises needs to be improved. Technological innovation capability still restricts the development of the company to a certain extent at this stage.

To further conduct cluster analysis on these 55 companies, this study divided the companies into two categories for comparative analysis from the perspectives of establishment years, enterprise attributes, and enterprise scale. The empirical results are shown in Table 4.[3]

5.2.1 Years of establishment

In this study, the 55 companies were divided into two categories according to the standard of establishment years greater than or equal to 20 years and less than 20 years. Because the average TFP shows 0.956 > 0.937, generally speaking, long-established companies have a higher level of operational efficiency than those more recently established. Under the condition that the change value of comprehensive technical efficiency is basically the same, the average technological progress change value of enterprises with a long establishment is higher than that of enterprises with a lower establishment period, that is, 0.958 > 0.939. This advantage is mainly reflected in the scale efficiency (1.003 > 0.997), implying that enterprises with a long establishment period tend to have more obvious scale benefits and more management experience. However, it can also be seen from the sample data that the change value of the pure technical efficiency of long-established enterprises is slightly lower than that recently established enterprises, which indicates that long-established enterprises should also give more focus to the amelioration of technical efficiency on the issue.

5.2.2 Enterprise attributes

In this study, the 55 fintech listed companies were divided into two categories according to whether they are state-owned enterprises. The empirical results are shown in Table 4.[4] Because the average TFP shows 0.95 > 0.94, in general, non-state-owned enterprises are more efficient than state-owned enterprises. The average change value of comprehensive technical efficiency of non-state-owned enterprises is slightly higher than that of state-owned enterprises (0.95 > 0.94), but the change value of technological progress is not significantly affected by enterprise attributes. In-depth analysis of the change value of comprehensive technical efficiency revealed that the pure technical efficiency value of non-state-owned enterprises is 1.004, while that of state-owned enterprises is 0.998, but the change value of the scale efficiency of non-state-owned enterprises is 0.996, and that of state-owned enterprises is 1. This shows that non-state-owned enterprises are relatively more advanced in technological innovation. The reason is that compared with the R&D department of state-owned enterprises, which pay more attention to the characteristics of form, non-state-owned enterprises have relatively stronger and richer incentives and face fewer obstacles regarding issues such as government cooperation and principal-agent. However, non-state-owned enterprises have lower returns to scale than state-owned enterprises, which may be because state-owned enterprises are relatively more efficient at scale and have more policy bias and support.

5.2.3 Enterprise size

According to the scale of enterprises, this paper divides 55 companies into two categories: large enterprises and small and medium-sized enterprises. The empirical results are shown in Table 4.[5] Large enterprises are higher than small and medium-sized enterprises in all indicators; that is, the TFP index of large enterprises is 0.952, greater than that of small and medium enterprises (0.929). The change value of the comprehensive technical efficiency of large enterprises is 1.004, while it is 0.991 for small and medium enterprises. The technological progress change value of large enterprises is 0.948, greater than small and medium-sized enterprises at 0.938, indicating that the operational efficiency of large-scale enterprises is generally higher than that of small and medium-sized enterprises and that they have more advantages in the operational efficiency of each subdivision.

5.2.4 Analysis of non-radial relaxation variables (SBM-DEA model)

When the traditional radial model analyses input redundancy or output deficiency, it suggests that input and output change in the same proportion, which makes the final efficiency value relatively inaccurate, and the size and magnitude of the adjustment of input and output indicators also varies. It is difficult to fully consider; thus, this study further uses the SBM-DEA model to analyse the financial data of the selected companies through the DEA-SOLVER Pro5.0 software. The relaxation variable (which mainly refers to the amount of input redundancy that needs to be reduced to achieve the optimal allocation) provides a path to improving the efficiency of listed companies in China's fintech sector.

The results show that among the 55 fintech listed companies in China, 26, 23, 22, 20, 18, and 21 companies are SBM-effective in each year from 2014 to 2019, respectively. This implies that the number of effective companies is relatively stable and basically maintained at 50% of the overall sample number; that is, about half of the listed fintech companies have achieved SBM effectiveness. In terms of the fluctuation of efficiency value of each company, Inspur, DHC Software, HengBao, Glodon, Rendong Holdings, Huahongjitong, Tianli Technology, Guao Electronic Technology, Hundsun Technologies, Fortune Trend Tech and other enterprises have always ranked first. Relatively speaking, the efficiency values and rankings of companies such as GRG Banking Equipment, Asia Link Technology, Great Chinasoft Technology, Hithink RoyalFlush Information Network, and Shanghai DZH have changed significantly.

Compared with the radial adjustment of the slack variables of the standard DEA model, the SBM-DEA model provides an index adjustment path and size for improving the efficiency of the SBM ineffective DMUs from a non-radial perspective.[6] In 2019, a total of 21 companies were SBM-effective. The input and output indicators of these companies basically do not need to be optimised, the slack variable is 0, the combination of factors is relatively reasonable, and there is no input redundancy.

The remaining 34 non-SBM-effective enterprises need to adjust the input or output variables. Overall, the input redundancy of non-SBM-effective enterprises is mainly total assets, payable employee compensation, and number of employees, and the output is also insufficient. It is mainly reflected in the variable of net profit. Taking China Information as an example, if the company wants to achieve effective SBM, it needs to reduce its total assets of 3.45-billion-yuan, employee compensation payable of 311 million yuan, and number of employees of 7,900. Fintech listed companies with ineffective SBM can effectively improve their operational efficiency by adjusting the input amount of each input element and the output target of each output.

6 Conclusions

The DEA model is used to analyse the operating efficiency and slack variables of 55 listed fintech companies from 2014 to 2019. This study differentiates between the establishment years, enterprise attributes, and scale of fintech companies. The empirical results of this study show that, first, the overall operational efficiency of Chinese fintech companies is not high. Excessive cost input sometimes cannot bring about profit growth but reduces the efficiency of capital use and generates losses for the company. Second, the final total factor productivity index is less than 1 no matter what kind of index system is used, indicating that the technological innovation capability still restricts the development of enterprises to a certain extent at this stage. Third, operational efficiency is heterogeneous. Enterprises with a long establishment period have higher operational efficiency than those with a short establishment period. In terms of comprehensive technical efficiency, under the condition that the change value is the same, the average technological progress change value of enterprises with a long establishment period is higher than that of enterprises with a shorter establishment period; non-state-owned enterprises have a higher level of operational efficiency than state-owned enterprises, and the average comprehensive technical efficiency change of non-state-owned enterprises is also slightly higher than that of state-owned enterprises. However, the attributes of the enterprise have no significant impact on the change value of technological progress. The operational efficiency of large enterprises is generally higher than that of small and medium-sized enterprises, and they have more advantages in the operational efficiency of each subdivision. Finally, the input redundancy of non-SBM effective enterprises is mainly reflected in total assets, payable employee compensation, and the number of employees, and the output deficiency is mainly reflected in the variable of net profit.

7 Recommendations

Multi-party cooperation can improve the overall operational efficiency of fintech companies. Fintech companies should focus more on increasing the utilisation of input factors rather than on the speed and size of their growth strategies. The proportion of input and output of factors should be adjusted, particularly the input of total assets, salary payable, and number of employees so as to achieve the optimal allotment efficiency. The benefits brought by scientific and technological innovation in the development process of the company should be considered, and policies should be formulated to encourage innovation.

Improving the operational efficiency of fintech companies also requires a sound regulatory system. Fintech itself has the property of cross-market and cross-industry development, which also demands higher requirements for cross-sector supervision. For the supervision of fintech businesses and products, a cross-departmental coordination mechanism must be established to jointly implement effective supervision. For regulatory authorities, enterprise innovation should be carried out under the compliance framework of prudent supervision. While supporting the improvement of the social and market efficiency of fintech, a strict regulatory bottom line should be established, and regulatory research on the fintech industry and the process of system construction should be promoted. After deeply mastering the basic business forms and industry characteristics of fintech, a scientific and effective regulatory system should be formulated, and investment in new technologies should be strengthened to promote enterprise development. At present, innovation ability restricts the development of fintech enterprises. These enterprises can increase investment in technology research and development, financial support, and other aspects to fully support the improvement of enterprises' efficiency.

A differentiated promotion strategy should be adopted. Fintech companies with different establishment years, enterprise attributes, and enterprise size can adopt differentiated promotion strategies. Long-established fintech enterprises should pay more attention to improving technical efficiency, while younger enterprises should learn advanced management experience from those with a long establishment period and constantly expand their scale and influence. State-owned fintech enterprises should improve their efficiency improvement measures, such as output incentives, so as to promote their ability to innovate and develop. Non-state-owned enterprises should actively cooperate with relevant departments in various regions to obtain certain welfare subsidies or policy support. Large fintech enterprises should give full play to their competitive advantages, continuously enhance their influence, and serve society, while small and medium-sized fintech enterprises should practice China's inclusive financial policies and fulfil their own social values.

Input factors and output targets should be adjusted. Among the 55 listed fintech companies, 21 are SBM-effective, while the remaining 34 that are not need to be adjusted in terms of input or output variables. Non-effective fintech listed companies can effectively improve their operational efficiency by adjusting the input amount of each input factor and the output target of each output.

8 Limitations and scope for future research

Restricted by objective factors, this paper has several shortcomings. At present, many fintech companies in China are not listed. Because the financial data of unlisted companies are not disclosed to the public, there are constraints such as difficulties in data collection. In this study, 55 listed companies in China's fintech concept sector were selected as the development representatives of fintech enterprises, but there are certain limitations in the selection of samples. In addition, due to subjective factors such as the author's research ability, the research results may also have certain limitations.

With the continuous development of fintech enterprises, an increasing number of companies will choose to go public in the future, and the financial data disclosed by fintech enterprises will increasingly tend to reflect the overall situation of the fintech industry. In addition, the outbreak of COVID-19 in 2020 and its persistence have had a substantial impact on the daily operations of almost all enterprises. The financial data of this period is of high research value, and it will be a valuable research direction to study the impact of COVID-19 on the operational efficiency of fintech enterprises. Therefore, it is believed that more comprehensive and systematic conclusions can be drawn if relevant research can expand data sources and develop more perfect analysis tools in the future.

Funding

This study is funded by the National Social Science Foundation Project 'Comparative Evaluation and Enhancement Mechanism of Financial Inclusion under Digital Empowerment' (Project No.: 21BJL087).

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Notes

1 The slack variable represents the amount of input that needs to be reduced to achieve the optimal configuration, and the residual variable represents the amount of output that needs to be increased to achieve the optimal configuration.

2 Due to space limitations, this and the following sections only show the empirical results of some companies; detailed data for all companies can be obtained by contacting the author.

3 Due to space limitations, the empirical results in this section only show the average value. The detailed data of each company can be obtained by contacting the author.

4 Due to space limitations, only the empirical results of some companies are shown here. The classification results for all companies can be obtained by contacting the author.

5 Due to space limitations, only the empirical results of some companies are shown here. The classification results for all companies can be obtained from the author.

6 Due to space limitations, the empirical results of the SBM slack variables of the 55 Chinese fintech companies from 2014 to 2018 are not shown here. If required, the author can be contacted for the data.