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Evaluation of mismatch effect of financing structure based on data envelopment analysis

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Data envelopment analysis is used to assess the mismatch effect of the financing structure of 26 listed companies in China's information technology industry from 2009 to 2016. The reasons for the change in efficiency are analysed through a decomposition of efficiency. The results show that the financing structure of listed companies in China's information technology industry is generally slightly mismatched, with problems of excessive financing and insufficient investment. Moreover, the financing structure is gradually deteriorating and the non-efficient financing is gradually increasing. It is suggested that the IT industry should reduce debt financing, enhance the operation capacity, and strengthen investment decision-making to alleviate an investment shortage.

Keywords: Data envelopment analysis, Financing structure, Listed companies, Mismatch effect

1. INTRODUCTION

It is a significant part of financial risk management to control the liquidity risk caused by the mismatch of investment and financing structure. This has to be done scientifically and reasonably. Due to different financing channels, the financing structure of companies is different, which leads to different capital costs. With the development of various business and investment activities, the mismatch risk of investment and financing structure is characterized by diversity and complexity (Dai, 2016). For a long time, the theoretical research on the financing structure and investment structure of companies has been in a state of divided and unbalanced development to some extent (Chen, 2011). Scholars usually consider the two problems separately and seldom discuss the matching relationship between investment and financing. In the limited research on the mismatch between investment structure and financing structure, scholars pay more attention to the mismatch effect of investment and financing maturity (Chen, 2009; Bai et al., 2016). However, the mismatch effect of corporate financing structure is not only in the time dimension. The maturity structure mismatch of investment and financing, but also the spatial dimension - the mismatch between the structure of capital use and the structure of financing source. That is, the mismatch effect has spatial and temporal characteristics (Li & Zhang, 2017). In order to understand the causes of the mismatch effect of financing structure and comprehensively control the mismatch degree, it is particularly important to evaluate the mismatch effect of the financing structure by integrating the space-time characteristics of mismatch effect of the financing structure.

Current research on the rationality of financing are mostly used in the evaluation of financing efficiency (Zhang & Zhang, 2016; Xue et al., 2016; Xie & Ma, 2016). However, the research on the mismatch effect of financing structure has not yet formed a reasonable and complete indicator system and evaluation criteria, which makes the research on the mismatch effect of financing structure lack of comprehensiveness and applicability. Therefore, it is one of the urgent problems in the field of liquidity risk management to develop a scientific and reasonable indicator system and evaluation model for the mismatch effect, so as to guide companies to accurately locate the mismatch risk of financing structure, and take corresponding measures to mitigate the financing risk.

2. FORMING-MECHANISM AND EVALUATION INDEXES

2.1 Forming-mechanism of mismatch effect of financing structure

The main sources of the mismatch effect of financing structure are the mismatch of capital use and financing sources, the maturity mismatch of investment and financing.

Financing sources include interest-bearing debt financing, commercial credit debt financing and equity financing. In general, for sustainable companies, the smaller the debt financing, the better. Because the smaller debt financing and the larger equity financing make the advantages that companies do not have to face higher debt repayment pressure, and do not have to pay too much attention to the financial distress caused by the inability to repay debts.

The maturity of financing includes both short-term financing and long-term financing. In general, for sustainable companies, the smaller the short-term financing is, the better. Because the smaller short-term financing and the larger long-term financing make the advantages that it is not easy to form the problem of “short-term financing and long-term investment”, so that companies do not have to face repayment of capital and interest in a short period of time. Meanwhile, they do not have to pay much attention to the financial distress caused by the inability to repay short-term debt. The forming-mechanism of mismatch effect of financing structure is shown in figure 1.

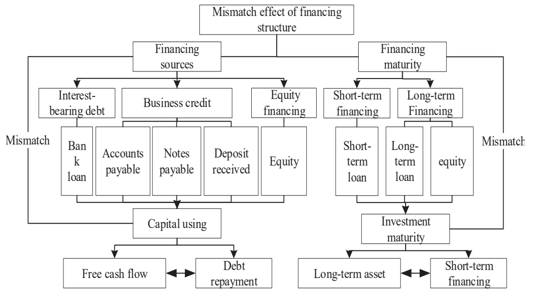

Figure 1 Forming-mechanism of mismatch effect of financing structure.

2.2 Evaluation Indexes

The index basis of DEA model measurement is input and output indexes. McLean & Zhao (2014) constructed the "investment-current liabilities" model to study the economic cycle and investor sensitivity based on the "investment-cash flow" sensitivity method (Fazzari et al, 1988). Drawing lessons from McLean & Zhao (2014), in order to further discuss companies’ mismatch problem of investment and financing and evaluate the mismatch effect, we choose the financing source structure indexes like total liabilities, interest-bearing debt, interest expense, equity and financing maturity structure indexes like net short-term financing, short-term loans, long-term financing as the input indexes. Meanwhile, output indexes consist of free cash flow, cash, working capital requirements and net value of fixed assets. Evaluation Indexes are shown in table 1.

Table 1 Evaluation indexes of mismatch effect.

Input indexes		Code	Output Indexes	Code
Financing source structure indexes	Total liabilities	in1	Free cash flow	out1
	Interest-bearing debt	in2		
	Interest expense	in3		
	Equity	in4		
Financing maturity structure indexes	Net short-term financing	in5	Cash	out2
	Short-term loan	in6	Working capital requirements	out3
	Long-term Financing	in7	Net value of fixed assets	out4

3. EVALUATION MODEL

In order to evaluate the mismatch effect of a financing structure, it is necessary to obtain the best financing structure, that is, to obtain the best free cash flow and investment appreciation with the smallest financing scale and the longest financing maturity, which is a problem of optimal allocation of resources. Data Envelopment Analysis (DEA) in the evaluation of resource allocation efficiency has several advantages such as multiple inputs and outputs, no preset parameters, no dimensional constraints, the Data Envelopment Analysis is selected as the main evaluation method in this research. DEA has undergone numerous improvements and transformations, and the most typical models are the C^2R model and the BC^2 model. Based on the C^2R model and the BC^2 model, the evaluation model of the mismatch effect of financing structure is constructed.

The financing structure mismatch (FSM_j) is used to represent the financing structure mismatch effect of the j company. The calculation is generally made by technical efficiency ($\alpha_{\text{tech}} - j$), average effective input rate $\overline{\alpha_{input-j}}$ and average effective output rate $\overline{\alpha_{output-j}}$ (zhang et al., 2014), as shown in formula 1.

$$FSM_j = \alpha_{tech-j} \times \overline{\alpha_{input-j}} \times \overline{\alpha_{output-j}} \tag{1}$$

Among them, technical efficiency, average effective input rate and average effective output rate are all calculated by the C^2R model and BC^2 model. Technical efficiency, known as overall efficiency, is the product of pure technical efficiency and scale efficiency. The decision unit with most efficient resource allocation has a technical efficiency of 1, indicating that the decision-making unit is in the best state of overall operation. Pure technical efficiency, known as allocation efficiency, is used to measure the rationality of resource allocation in decision units. The higher the pure technical efficiency is, the more effective the decision-making unit is in using input resources to maximize output. Scale efficiency is used to measure whether the decision unit reaches the optimal state of input and output. The higher the scale efficiency is, the greater the production efficiency is. The average effective input rate represents the average effective input rate of the j company, which is calculated in formula 2. The average effective output rate is the same as this principle. Because $0 \leq \alpha_{tech-j} \leq 1$, $0 \leq \overline{\alpha_{input-j}} \leq 1$, $0 \leq \overline{\alpha_{output-j}} \leq 1$, therefore $0 \leq FSM_j \leq 1$.

$$\overline{\alpha_{input-j}} = \sum_{i=1}^{n} \alpha_{input-ij}/n \tag{2}$$

Through DEA analysis, we can also get the effectiveness of various input indexes which is the degree to which each input of decision-making unit plays a role according to the level of the same industry. Assuming that the actual input amount is X_i and the input redundancy amount is ΔX_i, the input redundancy rate and the effective input rate are respectively shown in formula 3 and formula 4.

$$\alpha_{input-i} = \Delta X_i / X_i \tag{3}$$
$$\beta_{input-i} = 1 - \Delta X_i / X_i \tag{4}$$

For each output index, DEA analysis can also get its deficiency, that is, the gap between the target output that the decision-making unit should achieve and the actual output of decision-making unit, that is, the improvement space of decision-making unit. Assuming the target output amount is Yi and the output deficit is Δ Yi, the output deficit rate and the effective output rate are respectively shown in formula 5 and formula 6.

$$\alpha_{output-i} = \Delta Y_i / Y_i \tag{5}$$
$$\beta_{output-i} = 1 - \Delta Y_i / Y_i \tag{6}$$

4. RESULTS AND ANALYSIS

4.1 Sample selection and data sources

(1) Selection of industry to be evaluated

Companies in different industries have different financing structures, and their mismatch standards are different. In order to ensure the homogeneity of the evaluation of the mismatch effect, it is advisable to select companies in the same industry. Throughout all industries in China, the information technology industry has a strong driving force and strong penetration to the other industries. Its rapid development can not only benefit itself, but also promote the development of the other industries. Compared with the traditional industry, the information technology industry is an industry with high investment, high risk and high profit. Due to the lack of collateral and the high rate of failure in R&D, commercial banks are particularly cautious about lending to companies in the industry. As a result, the financing channels of information technology companies are relatively narrow, and the unreasonable financing structure is more prominent. Therefore, this research selects information technology industry as sample industry for the evaluation of mismatch effect of investment and financing structure.

(2) Selection of sample companies to be evaluated

The following principles are followed in the selection of specific samples: (1) select only A-share listed companies: (2) select only listed companies of similar size: (3) only listed companies with complete data are selected (4) exclude ST, *ST and PT companies. Therefore, 26 listed companies in the information technology industry are selected as decision-making units (DMU).

(3) Data sources

The research data are panel data of 208 observed financing structures of 26 listed companies in the information technology industry from 2009 to 2016.The data source is CSMAR database, and the related analysis is completed with DEAP2.1.

4.2 Indexes pre-processing

When using the DEA model to evaluate the mismatch effect of investment and financing structure, the following requirements are put forward for the analysis data: (1) the numerical values of the research indexes are non-negative and non-zero; (2) the input variables are generally that “smaller is better”, and the output variables are generally that “bigger is better”. However, there are negative number and zero in the indexes in table 1. At the same time, in the input indexes, the in4 and in7 belong to the indexes that “bigger is better”, in the output indexes, the out3 belongs to the indexes that “smaller is better”, which runs counter to the requirements of the DEA to the data. Therefore, it is necessary to standardize the indexes. Indexes preprocessing follows the following rules: if an input index belongs to “bigger is better” type, using formula 7. If it belongs to the “smaller is better” type, the formula 8 is adopted. Thus, the input indexes after preprocessing satisfies $1 \leq in_i' \leq 10$, and all belong to the “smaller is better” type.

$$in_i' = 10^{(in_{imax} - in_i)/(in_{imax} - in_{imin})} \tag{7}$$
$$in_i' = 10^{(in_i - in_{min})/(in_{max} - in_{min})} \tag{8}$$

If an output index out_i belongs to "the bigger the better" type, the formula 9 is adopted. If it belongs to the "smaller is better" type, the formula 10 is adopted. Thus, the output indexes after preprocessing satisfies $1 \leq out_i' \leq 0$, and all belong to the "bigger is better" type.

$$out_i' = 10^{(out_i - out_{imin})/(out_{imax} - out_{imin})} \quad (9)$$

$$out_i' = 10^{(out_{imax} - out_i)/(out_{imax} - out_{imin})} \quad (10)$$

4.3 Technical efficiency analysis

The pre-processed data of 26 listed companies from 2009 to 2016 are imported into the software DEAP2.1 for calculation, so as to obtain the technical efficiency analysis results of the financing structure mismatch effect based on C^2R model and BC^2 model, including the results from 2009 to 2016. Take 2016 as an example, as shown in Table 2.

Table 2 Technical efficiency analysis in 2016.

DMUs	Technical efficiency	Pure technical efficiency	Scale efficiency
DMU1	0.996	1	0.996
DMU2	0.982	0.987	0.994
DMU3	0.971	0.982	0.989
DMU4	0.991	0.995	0.996
DMU5	0.983	0.999	0.983
DMU6	1	1	1
DMU7	1	1	1
DMU8	0.99	0.998	0.991
DMU9	0.962	0.998	0.964
DMU10	0.966	0.989	0.977
DMU11	0.985	1	0.985
DMU12	0.996	1	0.996
DMU13	0.977	0.988	0.989
DMU14	0.989	1	0.989
DMU15	0.994	0.999	0.996
DMU16	0.967	0.977	0.99
DMU17	1	1	1
DMU18	0.954	0.965	0.988
DMU19	0.985	0.999	0.985
DMU20	0.99	1	0.99
DMU21	0.993	0.998	0.995
DMU22	0.987	0.992	0.994
DMU23	1	1	1
DMU24	0.996	0.997	0.999
DMU25	0.981	1	0.981
DMU26	0.975	0.988	0.987
Mean	0.985	0.994	0.991

Technical efficiency analysis involves the pure technical efficiency and scale efficiency analysis: in terms of pure technical efficiency analysis, in the 26 listed companies, there are 10 companies whose pure technical efficiency is 1. It indicates that these companies achieve the optimal resource allocation efficiency and has a good ability of financing management. For 16 listed companies with pure technical efficiency less than 1, their resource management level needs to be improved. According to the analysis of scale efficiency, among the 26 listed companies, 4 listed companies have scale efficiency of 1, that is, reach the optimal input and output scale, indicating that these listed companies have the appropriate financing scale and reach the optimal production scale. For 22 listed companies whose scale efficiency is less than 1, their financing scale should be appropriately controlled to improve their production efficiency. From the overall perspective, it can be seen from table 2 that only 4 companies among the 26 listed companies have technical efficiency of 1, accounting for 15% of the total number, that is, 85% (100% to 15%) of the information technology listed companies do not have ideal financing structure matching in 2016.

4.4 Analysis of effective input rate and effective output rate

DEA inefficient decision-making unit must have the problem of redundant input or insufficient output. According to this, we can calculate the adjustment amount of the input and output indexes of each DEA inefficient decision-making units, and get the improvement direction of the financing input and the improvement space of the output. According to the model of effective input and effective output, analysis of the 26 listed companies in information technology industry is carried out. The results in 2016 are shown in table 3 and 4. From the perspective of effective input analysis, the results show that 19 listed companies have the problem of excessive investment, that is, these listed companies have not reached the optimal level in input indexes of financing structure, and there is a large optimization space. The other 7 listed companies formed a good investment scale. It can be seen from the average effective input rate in table 3 that the effective input of the 26 listed companies is the total liabilities, followed by short-term loan, while relatively large invalid input exists in the net short-term financing. From the perspective of effective output analysis, it can be seen from table 4 that the average effective output rate of cash is the lowest (90.8%), which indicates that 26 listed companies have a large space to improve their cash holdings in general. Meanwhile, net fixed asset output (99.4 per cent) is relatively well represented.

4.5 Evaluation of mismatch effect

Taking DMU2 as an example and using formula 1, its "financing structure mismatch effect" is:

$$FSM_2 = \alpha_{tech} \times \overline{\alpha_{input}} \times \overline{\alpha_{output}} = 0.982$$

$$\times 88.3\% \times 88.3\% = 0.791$$

The data of 26 listed companies in the information technology industry from 2009 to 2016 were respectively evaluated for the mismatching effect of financing structure, and the degree of mismatching of financing structure of listed companies in the information technology industry was obtained, as shown in table 5.

From the perspective of the changing trend of the mean, as shown in figure 2. The mismatch of the financing structure in the industry as a whole shows a downward trend, which indicates that after the financial crisis in 2008, the financing structure of listed companies in the information technology

Table 3 Results of effective input of financing structure.

DMUs	Effective input rate ($\alpha_{output-ij}$)							Average effective input rate ($\overline{\alpha_{input-j}}$)
	in1	in2	in3	in4	in5	in6	in7	
DMU1	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
DMU2	100.0%	85.5%	89.5%	88.4%	73.7%	89.2%	91.6%	88.3%
DMU3	100.0%	92.7%	82.3%	94.9%	82.2%	100.0%	100.0%	93.2%
DMU4	100.0%	99.6%	99.1%	99.9%	99.2%	99.6%	100.0%	99.6%
DMU5	100.0%	99.8%	94.6%	89.4%	86.2%	100.0%	90.7%	94.4%
DMU6	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
DMU7	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
DMU8	100.0%	99.6%	97.6%	99.5%	100.0%	99.6%	99.5%	99.4%
DMU9	98.7%	100.0%	98.4%	97.3%	100.0%	100.0%	97.3%	98.8%
DMU10	99.1%	100.0%	92.5%	98.3%	95.2%	99.9%	99.1%	97.7%
DMU11	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
DMU12	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
DMU13	99.8%	99.3%	98.4%	99.5%	99.1%	100.0%	99.8%	99.4%
DMU14	99.6%	100.0%	98.9%	99.6%	95.6%	100.0%	99.6%	99.0%
DMU15	100.0%	99.9%	99.2%	100.0%	97.4%	99.9%	100.0%	99.5%
DMU16	100.0%	95.1%	93.1%	98.4%	94.2%	95.4%	98.7%	96.4%
DMU17	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
DMU18	100.0%	94.7%	91.4%	97.4%	88.2%	96.7%	100.0%	95.5%
DMU19	100.0%	99.2%	94.0%	94.8%	90.7%	100.0%	95.3%	96.3%
DMU20	99.6%	100.0%	98.8%	99.6%	96.3%	100.0%	99.6%	99.1%
DMU21	99.9%	100.0%	99.1%	99.4%	98.5%	99.9%	99.5%	99.5%
DMU22	100.0%	99.2%	97.2%	100.0%	96.2%	99.1%	100.0%	98.8%
DMU23	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
DMU24	100.0%	98.2%	93.1%	94.2%	88.2%	99.9%	95.4%	95.6%
DMU25	99.0%	100.0%	98.4%	98.8%	97.2%	100.0%	98.7%	98.9%
DMU26	99.7%	100.0%	98.5%	99.6%	97.2%	99.9%	99.7%	99.2%
Mean	99.8%	98.6%	96.7%	98.0%	95.2%	99.2%	98.6%	98.0%

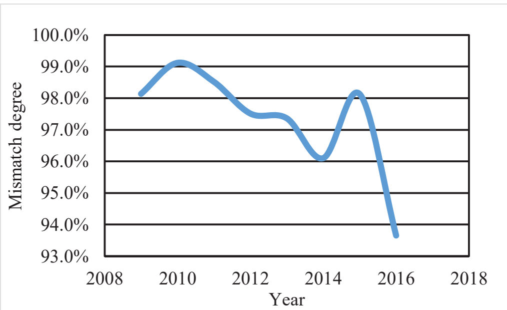

Figure 2 Mismatch degree of financing structure in information technology industry.

industry is gradually deteriorating, the non-efficient financing is gradually increasing, and there are generally problems of excessive financing and insufficient investment. Therefore, the information technology industry should strengthen the management of financing, operation and investment, reduce debt financing, especially interest-bearing debt financing and short-term financing, enhance the operation capacity, strive to improve the free cash flow, and strengthen investment decision-making to alleviate the shortage of investment.

In terms of distribution, the mismatch degree of financing structure can be divided into four different grades: "severe mismatch", "moderate mismatch", "slight mismatch" and "matching". According to table 8, the annual minimum of financing structure mismatch degree FSM_{min} can be seen from 2009 to 2016 respectively, and the maximum FSM_{max}=100%. If FSM=100%, it indicates that the company has the optimal allocation of financing resources and the financing structure reaches the optimal matching state. Thereby, the lower FSM is, the greater the mismatch degree is. Accordingly, this research takes $FSM_{matching}$=100% as the standard of matching, take the $FSM_{moderate}$= $FSM_{matching}$- 2/3 × ($FSM_{matching}$- FSM_{min}) as the critical value of moderate mismatch, when FSM<$FSM_{moderate}$,the financing structure is in the state of "severe mismatch". In addition, this research takes the FSM_{slight}= $FSM_{matching}$- 1/3 × ($FSM_{matching}$- the FSM_{min}) as the critical value of "slight mismatch". The distribution range of critical value of mismatch effect of listed companies in information technology industry is shown in table 6.

According to table 6, the distribution of the financing structure mismatch degree of 26 listed companies in the information technology industry can be determined, as shown in table

Table 4 Results of effective output of financing structure.

DMUs	Effective output rate				Average effective output rate
	out1	out2	out3	out4	
DMU1	100.0%	100.0%	100.0%	100.0%	100.0%
DMU2	100.0%	65.8%	100.0%	99.0%	91.2%
DMU3	86.8%	63.4%	94.9%	100.0%	86.3%
DMU4	100.0%	98.1%	99.8%	100.0%	99.5%
DMU5	100.0%	70.2%	98.6%	97.6%	91.6%
DMU6	100.0%	100.0%	100.0%	100.0%	100.0%
DMU7	100.0%	100.0%	100.0%	100.0%	100.0%
DMU8	95.0%	99.3%	99.1%	99.7%	98.3%
DMU9	100.0%	98.9%	92.5%	96.7%	97.0%
DMU10	89.8%	87.7%	98.1%	98.8%	93.6%
DMU11	100.0%	100.0%	100.0%	100.0%	100.0%
DMU12	100.0%	100.0%	100.0%	100.0%	100.0%
DMU13	98.8%	96.4%	98.8%	99.7%	98.4%
DMU14	99.8%	88.9%	100.0%	99.4%	97.0%
DMU15	100.0%	93.9%	99.8%	100.0%	98.4%
DMU16	99.2%	100.0%	98.8%	99.1%	99.3%
DMU17	100.0%	100.0%	100.0%	100.0%	100.0%
DMU18	100.0%	81.7%	96.9%	98.8%	94.4%
DMU19	100.0%	79.2%	97.3%	98.3%	93.7%
DMU20	95.4%	90.6%	100.0%	99.8%	96.4%
DMU21	99.7%	96.7%	99.9%	100.0%	99.1%
DMU22	100.0%	92.7%	99.6%	99.7%	98.0%
DMU23	100.0%	100.0%	100.0%	100.0%	100.0%
DMU24	94.3%	73.5%	100.0%	100.0%	91.9%
DMU25	100.0%	91.1%	98.3%	99.4%	97.2%
DMU26	100.0%	92.7%	98.3%	99.5%	97.6%
Mean	98.4%	90.8%	98.9%	99.4%	96.9%

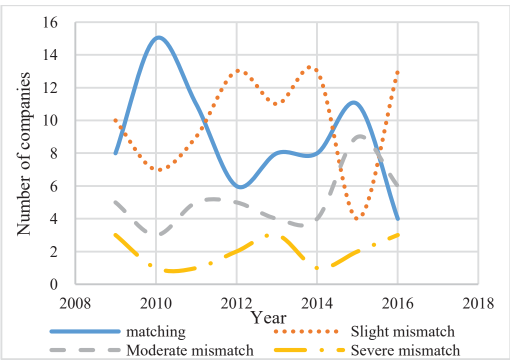

Figure 3 Distribution of financing structure mismatch in information technology industry.

7 and figure 3.

From table 6, 7 and figure 3, the number of companies with matching financing structure in information technology industry accounts for only half of the total from 2009 to 2016. It is shown that China's information technology industry is generally in a state of slight mismatch, followed by the number of companies with moderate mismatching financing structure. In addition, since 2010, the number of companies with matching financing structure in China's information technology industry has been decreasing year by year, and the number of companies with slight mismatching financing structure has been increasing year by year, which further indicates that the financing structure of China's information technology industry is gradually changing to mismatch and is deteriorating year by year.

5. CONCLUSION

As two basic financial activities of a company, investment and financing activities are closely related to each other. Based on the above empirical analysis on the evaluation of the mismatch effect of investment and financing structure of listed companies in information technology industry, the following conclusions are drawn in this research. Firstly, the mismatch effect of investment and financing has spatial and temporal characteristics, included the financing maturity structure mismatch and financing source structure mismatch. Secondly, the data envelopment analysis method is used to build evaluation model, which can directly analyze and evaluate the mismatch effect of financing structure. Thirdly, the financing structure of listed companies in China's information technology industry is generally in a state of slight mismatch, with problems of excessive financing and insufficient investment. Moreover, the financing structure is gradually deteriorating and inefficient financing is gradually increasing. Therefore, information technology companies should strengthen the management of investment and financing. For companies with mismatch of financing source structure, they should pay attention to the enhancement of their operating capacity, increase free cash flow,

Table 5 Mismatch degree of financial structure of the listed companies from 2009 to 2016.

DMUs	2009	2010	2011	2012	2013	2014	2015	2016
DMU1	99.5%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.6%
DMU2	100.0%	100.0%	98.0%	100.0%	88.7%	74.6%	100.0%	79.1%
DMU3	100.0%	100.0%	100.0%	98.9%	100.0%	100.0%	99.5%	78.0%
DMU4	98.1%	99.0%	98.6%	98.6%	97.8%	98.5%	98.2%	98.2%
DMU5	98.4%	98.7%	96.8%	94.8%	96.3%	99.0%	95.4%	85.0%
DMU6	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
DMU7	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
DMU8	95.4%	98.4%	98.1%	98.8%	99.1%	98.0%	99.3%	96.7%
DMU9	93.5%	97.6%	96.8%	94.7%	95.8%	98.2%	100.0%	92.3%
DMU10	96.7%	97.7%	95.6%	93.2%	90.2%	89.9%	96.0%	88.4%
DMU11	99.8%	100.0%	100.0%	99.9%	100.0%	100.0%	100.0%	98.5%
DMU12	99.9%	100.0%	100.0%	98.3%	100.0%	100.0%	100.0%	99.6%
DMU13	96.3%	98.4%	97.1%	96.8%	94.1%	96.8%	97.5%	95.6%
DMU14	99.7%	100.0%	100.0%	99.9%	99.8%	99.8%	100.0%	95.0%
DMU15	97.5%	99.4%	99.1%	98.6%	99.5%	98.8%	98.5%	97.4%
DMU16	100.0%	100.0%	97.7%	96.9%	95.4%	89.6%	96.8%	92.6%
DMU17	93.1%	96.7%	100.0%	100.0%	99.8%	99.8%	100.0%	100.0%
DMU18	97.2%	100.0%	98.0%	97.7%	99.8%	87.4%	96.7%	86.0%
DMU19	100.0%	100.0%	99.1%	98.7%	92.5%	93.2%	92.8%	88.9%
DMU20	100.0%	100.0%	100.0%	99.4%	98.8%	98.5%	97.6%	94.6%
DMU21	98.4%	98.3%	96.1%	97.8%	98.9%	98.1%	97.1%	97.9%
DMU22	100.0%	93.7%	92.4%	89.6%	91.1%	92.5%	95.3%	95.6%
DMU23	99.8%	100.0%	100.0%	91.2%	100.0%	100.0%	100.0%	100.0%
DMU24	92.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	87.5%
DMU25	97.2%	100.0%	98.7%	95.2%	96.3%	87.9%	93.0%	94.3%
DMU26	98.9%	99.0%	99.3%	96.2%	97.5%	96.7%	97.4%	94.4%
Mean	98.1%	99.1%	98.5%	97.5%	97.4%	96.1%	98.1%	93.7%

Table 6 Critical value of mismatch effect.

Year	Matching	Slight mismatch	Moderate mismatch	Severe mismatch
2009	= 100%	[97.3%, 1)	[94.6%, 97.3%)	[0, 94.6%)
2010	= 100%	[97.9%, 1)	[95.8%, 97.9%)	[0, 95.8%)
2011	= 100%	[97.5%, 1)	[94.9%, 97.5%)	[0, 94.9%)
2012	= 100%	[96.5%, 1)	[93.1%, 96.5%)	[0, 93.1%)
2013	= 100%	[96.2%, 1)	[92.4%, 96.2%)	[0, 92.4%)
2014	= 100%	[91.5%, 1)	[83.1%, 91.5%)	[0, 83.1%)
2015	= 100%	[97.6%, 1)	[95.2%, 97.6%)	[0, 95.2%)
2016	= 100%	[92.7%, 1)	[85.4%, 92.7%)	[0, 85.4%)

Table 7 Statistics of financial structure mismatch in information technology industry

Mismatch degree	Mismatch companies							
	2009	2010	2011	2012	2013	2014	2015	2016
Matching	8	15	11	6	8	8	11	4
Slight mismatch	10	7	9	13	11	13	4	13
Moderate mismatch	5	3	5	5	4	4	9	6
Severe mismatch	3	1	1	2	3	1	2	3

and reduce unnecessary financing. For companies with mismatch of financing maturity structure, investment decisions should be strengthened to alleviate the shortage of investment.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

NOTES AND PHOTOS OF CONTRIBUTORS

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