Proceedings of the 2023 International Conference on Management Research and Economic Development
DOI: 10.54254/2754-1169/20/20230177

Predicting Fraud in U.S. - Listed Chinese Companies: An Empirical Analysis Based on M-Score and F-Score Models

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Abstract: M-Score and F-Score are financial fraud prediction models that are commonly used in Western capital markets. In this paper, we calculate M-Scores and F-Scores for each dataset of 15 fraudulent Chinese companies (including Hong Kong companies) listed in the U.S. from 2006 to 2020 and compare their M-Scores and F-Scores with 15 companies in the same industry that are not fraudulent. Firstly, we used Student's t-test on data from both models respectively. The result shows that both of them are able to predict fraud well for Chinese stocks listed in the U.S. With the result, we further compare and test the differences between the financial fraudulent samples and the comparison samples in the dimensions of each variable in the M-Score and F-Score models. Finally, we draw a result that they are effective in predicting whether a Chinese company committed financial fraud.

Keywords: M-Score, F-Score, U.S.-listed Chinese companies, predictive models, financial fraud

1. Introduction

1.1. Study Background and Purpose

According to the relevant regulations of the U.S. Securities and Exchange Commission (SEC), listed companies are required to publicly disclose financial information on a regular basis. Theoretically, the disclosure of financial information should be beneficial to investors of listed companies. Financial information disclosure enables investors to receive information, fully understand the specific situation of the company, to a certain extent, reduce the information asymmetry between listed companies and investors, reduce the moral hazard of the company, which should be rewording to both companies and investors.

However, news of falsification by Chinese listed companies continues to emerge. Since 2000, more and more listed companies have been exposed to financial fraud. The material omission of information disclosure by listed companies has indeed made investors have great doubts about the authenticity of the financial reports of listed companies. In fact, financial fraud is not only a problem in China's securities market but also a severe problem in the securities markets of many countries in the world, such as the famous Enron Corporation in the United States, which misrepresented its profits by 586 million in a few years [1].

The good operation of the capital market cannot be achieved without open, transparent, and true information disclosure, and the endless and diverse methods of financial fraud have brought huge losses to investors in the capital market and hindered the healthy development of the capital market. How to determine companies that may commit financial fraud through company characteristics in advance has become an important issue of common concern for practical circles, capital market regulators, and academics.

For present purposes, M-Score and F-Score models are commonly used in Western practice, using thresholds to quickly determine the likelihood of financial fraud in listed companies. However, for now, there is no evidence that the financial fraud models generated by Western research have good predictive power for the U.S. -listed Chinese companies. We hope to conduct a comprehensive review and examination of the financial fraud values developed in U.S. and Chinese companies listed in the US, and ultimately verify whether M-Score and F-Score are effective in predicting the presence of fraud in companies.

This paper collected 15 U.S. -listed Chinese companies (all listed in the United States) that were confirmed and exposed to committed financial fraud. We calculate the M-Score and F-Score of those companies and compare them to those who are in the same industry as the sample companies we chose's M-Score and F-Score, and analyze the difference between those who committed fraud and those who didn't, to see if the two scores can effectively identify the percentage of companies committed fraud.

1.2. Literature Review

The establishment of transparent, fair, and efficient capital markets is a common goal for all market participants and regulators. Between 1999 and 2002, a large number of financial fraudulent companies broke out in the United States, such as Enron and WorldCom, which caused incalculable losses to investors and employees in the market [2]; while the early exposure of financial fraudulent companies in China, such as Yin Guangxia, Ke Long, Lan Tian, Liang Mianzhen [3], and Wanfu Science [4], caused great damage to the credibility of domestic companies and hindered the healthy development of the domestic capital market. The practice of forensic accounting has been widely used in securities fraud cases in the United States. Forensic accounting refers to the scientific and artistic method of systematically studying the financial information of a company in order to detect deviations from normal operating conditions or the possibility of financial fraud and has been used to effectively detect several cases of financial fraud [5]. Many experts began to study models that could determine whether a company had committed financial fraud. However, in the last decade or so, the most influential model for predicting financial fraud has been the M-Score model [6], which was built entirely from financial data and is known for its success in predicting Enron fraud before the outbreak of Enron. Dechow et al. developed the F-Score (F1-score), financial fraud prediction model based on the M-Score by collecting a sample of 676 companies identified as fraudulent in the Accounting and Auditing Enforcement Releases (AAERs) issued by the SEC from 1982 to 2005. They examined the characteristics of fraudulent companies in five areas: accruals, financial indicators, non-financial indicators, off-balance sheet operations, and market information. They found that the model including only financial statement indicators had the best ability to determine financial fraud, with 69% accuracy [7].

DOI: 10.54254/2754-1169/20/20230177

1.3. Reasons and Methods of Financial Fraud

1.3.1. Reasons for Financial Fraud.

The fraud triangle theory proposed by Donald Creasey in 1953 states that there are three factors for committing fraud [8].

1.3.1.1. Pressure.

Pressure is the motive that could lead a person or a company to engage in deception, as demonstrated by Donald Cressey in 1953. It's possible that the strain comes from the workplace environment or from personal issues like debt or addiction. Management or other employees may be under pressure or offered incentives to commit fraud. People may be driven to affect results or put pressure on others to do so, for instance, if salary or promotion is strongly impacted by personal, divisional, or corporate success. Banks, investors, and other financial organizations may also put pressure on a company by making unrealistic demands [9].

1.3.1.2. Opportunity.

While pressure provides the impetus for crime, the individual or business must also believe in the possibility that the crime will go unnoticed. This hypothetical opportunity is the second element. In Cressy's view, the obvious opportunity to create deception consists of two components: substantial knowledge and technical skills. The general message is the awareness that the employee's position of trust may have been violated. Technical qualification refers to the qualification required to implement the breach. In most cases, a person or a firm must own these properties in order to be employed and retain his or her position.

1.3.1.3. Rationalization.

The final and third component of fraud is rationalization. Cressy emphasized that rationalization cannot be used to justify after the fact a theft has already occurred. It is important to remember that rationalization plays an important role in the preparation of the crime; in fact, it contributes to the motive for the crime. The embezzler who does not view himself as a criminal must first defend his crime. Justification is required so that the offender may defend his unlawful behavior to himself and keep up his impression of himself as a reliable person.

1.3.1.4. Capacity of CEO.

According to Wolfe and Hermanson [10], even though three fraud factors—pressure, opportunity, and rationalization—support fraud, a person's personality and personal skills also have a significant impact on whether or not fraud occurs. Wolfe and Hermanson said that the prospect of fraud can be realized if the CEO of the firm has the technical knowledge to recognize and take advantage of the flaws in the company's current internal controls. Therefore, a key aspect in deciding whether the gaps in internal control would ultimately result in fraud is the CEO's capacity.

1.3.2. Methods of Financial Fraud.

Fraud committed by business leaders can be categorized into three types [11].

1.3.2.1. Asset Theft Committed Fraudulently.

Most illicit asset theft is carried out through so-called related party transactions, in which the culpable manager initiates financial or commercial transactions between the company he supervises and its subsidiaries. Such investment plans are not subject to the authority or approval of the board of directors. As a result, the manager may be instructed to invest without supervision in companies that are about to fail.

1.3.2.2. Processing of Financial Statements.

The most common types of financial statement manipulation are excessive or unreasonably exaggerated revenue recognition, undervaluing operating expenses, and overvaluing assets [12,13]. Given the sheer number of events, prosecutions and counter-prosecutions that define the topic, it is impossible to estimate the number of accounting and financial manipulations of businesses. However, the available evidence suggests that, in general, it seems challenging to verify accounting or financial facts, including increases in earnings.

1.3.2.3. Absence of Misleading Disclosures.

When corporate executives fail to make the required financial and accounting disclosures, companies can face fines of up to millions of dollars. Undoubtedly, frauds like embezzlement and manipulation will not occur if the disclosure process of the company is carried out according to the standards and transparency required by the regulations [14]. The notes to the financial statements must be examined and contrasted with the balance sheet and financial statements in order to spot any abnormalities or verify the accuracy of this data.

2. Samples and Variables

2.1. Data Source and Sample Selection

2.1.1. Processing and Source of Fraud Sample Data.

The sample of financial fraud companies in this paper comes from the financial fraud incidents of Chinese companies listed in the United States identified by the US Securities Regulatory Commission and stock exchanges from 2006 to 2020. Financial fraud mainly involves exaggerated income, fabricated profits, under-calculated expenses, Inflated assets and related party transactions. In order to obtain more reliable data, the author consulted the SEC official website, the New York Stock Exchange official website, East Money, Yahoo Finance and the official websites of various companies and finally decided to choose the Wind database as the data source of the sample model in this paper. In the process of screening samples, in order to narrow down the scope from 356 listed companies (until October 2022), the author first referred to the short-selling report of 50 companies accused of financial fraud provided by American short-selling agencies such as Muddy Water and Citron. And then extract 15 companies with clear financial fraud, including 12 companies that were delisted due to fraud, and 3 companies that still exist in the stock market. In order to study the change data of the sample, the author collected the financial data of the fraudulent companies that have been delisted for the first three years except the year of financial fraud and collected the financial data of the two companies that still have US stock data for the first three to four years and the last three years of fraud. According to the financial data, 52 incidents of financial fraud in the annual reports of Chinese companies listed in the United States were finally screened out, involving a total of 15 companies. Due to the long history of some companies, it is worth noting that the time of sample data

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falsification is the final disclosure time of announcement violations and the actual time of financial falsification of the company is not disclosed, so the data has certain limitations.

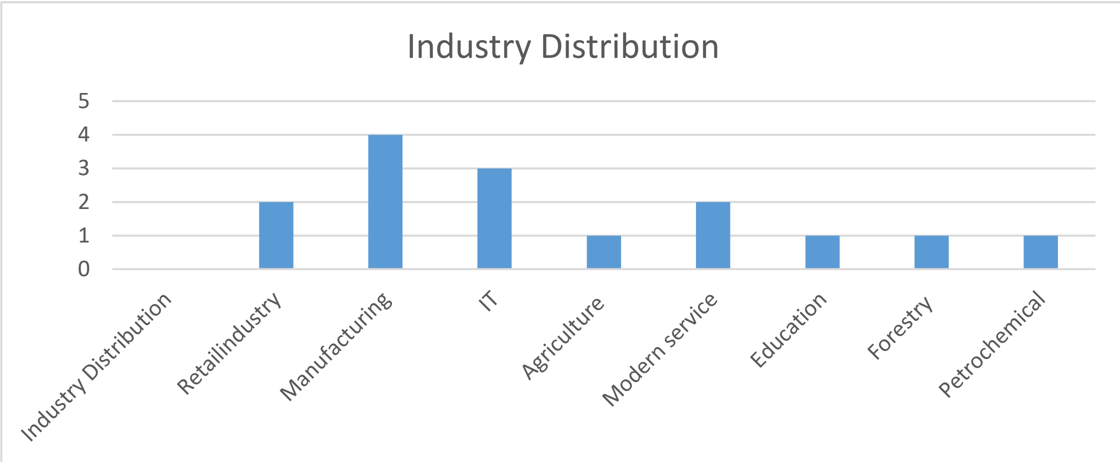

Figure 1: Industry distribution of fraud samples.

As shown in figure 1, for the sample industry distribution, when we select the company, we cover as many industries as possible, including retail industry, manufacturing industry, information technology (IT) industry, agriculture, modern service industry, education industry, forestry and petrochemical industry, in which manufacturing accounts for more than other industries, and IT industry accounts for the second largest proportion. This is also in line with the trend of economic development dominated by manufacturing and information technology (IT).

2.1.2. Data Sources of Fraud Company.

For each match sample of fraud companies, the author's preferred target is to select American companies listed in China in the same time period and in the same industry. However, due to the small number of these 356 listed companies (until October 1, 2022), the listing time varies, and the industry distribution is scattered, there are problems in the matching process, such as difficult industry matching and time intervals. Therefore, we expanded the scope of the match sample to include companies listed in the US and Hong Kong into the screening range. We used the company's market capitalization, time of listing, and main business as references in the industry classification on the East money, Yahoo Finance and Wind Databases. Finally, 52 matching samples and 15 companies were obtained. The matching principle is that a fraud sample corresponds to a non- fraudulent sample.

In the end, the author selected a total of 52 fraudulent samples, a total of 15 Chinese companies listed in the United States; 52 non-fraudulent samples, a total of 15 companies listed in the United States. The total number of samples is 104.

3. Materials and Methods

3.1. Definition of M-Score and F-Score

The M-Score model is a multi-factor based financial manipulation detection model, which uses a probability model to evaluate the possibility of financial manipulation for a given financial report and statement. Beneish [6] collected 74 US listed companies that were investigated and punished by the US Securities and Exchange Commission from 1982 to 1992 and were reported by the media and caused financial restatements as samples, used financial statement data to construct variables to study financial manipulation. The impact of the behavior and the preconditions that might motivate firms to undertake such activities are matched with a control group of 2332 companies in the corresponding industry for the corresponding period. After the Enron incident in 2001, M-Score had relatively accurately predicted the possibility of its financial fraud before the incident broke out.

The model of M-Score is shown in Equation (1) and Table 1.

Predictive value = -4.840 + 0.920*DSRI + 0.528*GMI + 0.404*AQI + 0.892*SGI + 0.115*DEPI - 0.172*SAI -0.327*LVGI + 4.679*TATA (1)

Table 1: M-Score variable definitions.

Variable	Formula
DSRI	Receivables/Sales
GMI	(Sales -COGS)/Sales
AQI	1 - ((Current assets + PP&E, net) Total assets)
SGI	Sales
DEPI	Depreciation/ (Depreciation + PPE, net)
SAI	SG&A/Sales
IVGI	(LT debt + Current liabilities)/Total assets
TATA	Total accruals/Total assets

Physical assets = (non-current assets - fixed assets - construction in progress - construction materials) / total assets.

F-Score model is a quantitative multi-factor prediction model, which can be used as a signal to warn potential profit manipulation and financial misstatement. Dechow et al. [7] on the basis of M-Score, the prediction model of F-Score financial fraud is established. They collected 676 samples of 1090 Accounting and Auditing Enforcement Releases (AAERs) issued by the Securities Regulatory Commission (SEC). Moreover, the main means of accounting fraud of listed companies in the United States is to increase income, undercharge and capitalize expenses.

The model of F-Score is shown in Equation (2), Equation (3) and Table 2

Predictive value = -7.893 + 0.790*rsst_acc + 2.518*ch_rec + 1.191*ch_inv + 1.979*soft_assets + 0.171*ch_cs – 0.932*ch_roa + 1.029*issue (2)

$$\text{F-Score}= [e^{Predicted\ value}/(1 + e^{Predicted\ value})\ ]/0.0037 \quad \text{where } e = 2.71828183 \tag{3}$$

Table 2: F-Score variable definitions.

Variable	Formula
rsst_acc	ΔNon-cash net operating assets/Average total assets
ch_rec	ΔReceivables/Average total assets
ch_inv	ΔInventory/Average total assets
soft_assets	(Total assets – PP&E, net – Cash & equivalents)/Total assets
ch_cs	% change in (Sales – ΔReceivables)
ch_roa	Change in ratio of Net income/Average total assets
issue	Equals 1 if LTD debt or common and/or preferred equity issued

Non-cash net operating assets defined as: Stockholders' equity – Preferred stock – Cash & equivalents

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3.2. Application of M-Score and F-Score

3.2.1. The Predictive Ability of M-Score and F-Score

3.2.1.1. The Predictive Ability of M-Score.

The M-Score threshold depends on the probability of making the first type of error (Type I Errors, misjudging a fraud company as a normal company) and the probability of making a second type of error (Type II Errors, misjudging a normal company as a fraud company). For this purpose, we use the t-test method to judge whether the M-Score of the 52 fraudulent samples is significantly different among the 104 overall samples. Assuming that the null hypothesis is that the difference between the fraud sample and the overall sample is not significant, the 95% confidence interval of the significance level is taken, and the calculation method is shown in Table 3.

Table 3: Paired differences of M-Score.

		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	Sig. (2-tailed)
					Lower	Upper			
Pair 1	Fraudulent samples - Total samples	1.023	2.152	0.307	0.405	1.641	3.327	48	0.002

P=0.002<0.05, the null hypothesis is rejected, and the fraudulent sample is significantly different from the overall sample. M-Score has a better ability to predict fraud among Chinese companies listed in the United States.

3.2.1.2. The Predictive Ability of F-Score.

We use two sample t-test methods to judge whether the F-Score of the 52 fraudulent samples is significantly different among the match samples. We assume that the null hypothesis is fraudulent sample is not significantly different from the match samples and take the 95% confidence interval of the significance level. The calculation is shown in Table 4.

Table 4: Paired differences of F-Score.

		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	Sig. (2-tailed)
					Lower	Upper			
Pair 1	Fraudulent samples - Total samples	0.675	1.3189	0.197	0.279	1.071	3.434	44	0.001

P=0.001<0.05, the null hypothesis is rejected, and the fraud sample is significantly different from the overall sample. F-Score has a better ability to predict fraud among Chinese companies listed in the United States.

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3.2.2. Descriptive Statistics of Fraudulent samples and Matching Samples

3.2.2.1. M-Score.

The author of the M-Score model mainly focuses on three types of indicators when selecting variables. The first type is financial indicators that affect investors' expectations of the company's future. The second type is related to the company's cash flow and company growth. The third type is based on contracts. incentives for financial fraud.

Table 5: Single variable test of M-Score.

	Fraudulent samples (1)		Match samples (2)		(1)-(2)	
	Mean	Median	Mean	Median	Difference of mean	Difference of median
DSRI	1.1446	0.9002	1.1528	1.0494	-0.0082***	-0.1492***
AQI	0.9741	1.0000	0.7871	0.4112	0.1870***	0.5888***
DEPI	1.0950	1.0000	1.0033	1.0000	0.0917***	0.0000***
TATA	0.0628	0.0369	-0.0575	-0.0313	0.1203***	0.0683***
GMI	1.0048	1.0000	0.9465	1.0041	0.0583***	-0.0041***
SGI	1.5709	1.3775	1.1467	1.1126	0.4241***	0.2649***
SGAI	1.2414	1.0294	0.9835	1.0000	0.2579***	0.0294***
LVGI	1.0382	0.9455	1.0152	0.9894	0.0230***	-0.0439***
M-SCORE	-1.6262	-1.9536	-2.6185	-2.6424	0.9923***	0.6888***

Notice: *p<0.1,**p<0.05,***p<0.01.

In order to compare and test the difference between the financial fraud sample and the control sample in each variable dimension in the obtained model, we compared the specific indicators of the fraud sample and the matching sample. Compared with the results of Beneish [6], the overall difference is small. Gross margin of fraud is greater than 1 and significantly greater than that of the control sample, the depreciation indicator is greater than 1, the depreciation rate of assets is lower, TATA is significantly higher than that of the matched sample, and selling and administrative expenses are higher. It also has more leverage. These differences are consistent with the results in Table 5.

3.2.2.2. F - Score

Table 6: Single variable test of F-Score.

	fraudulent samples (1)		Match samples (2)		(1)-(2)	
	Mean	Median	Mean	Median	Difference of mean	Difference of median
rsst_acc	0.0675	0.0943	-0.0054	0.0133	0.0729	0.0811**
ch_rec	0.0328	0.0141	0.0023	0.0008	0.0305***	0.0133***
ch_inv	0.0117	0.0027	0.0028	0.0000	0.0089	0.0027
soft_assets	0.5640	0.5738	0.5870	0.6288	-0.0230	-0.0550
ch_cs	0.2533	0.2834	0.0324	0.0900	0.2209	0.1934**
ch_roa	0.0140	0.0103	0.0016	0.0023	0.0125	0.0079
issue	0.9350	1.0000	0.7170	1.0000	0.2174***	0.0000***
F-Score	1.6341	1.1632	0.9590	0.6925	0.6752***	0.4707***

Notice: *p<0.1,**p<0.05,***p<0.01

Table 6 compares and tests the differences between the financial fraudulent samples and the comparison samples in the dimensions of each variable in the obtained model. Change in non-cash

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net operating assets (rsst_acc), Change in receivables (ch_rec), Change in cash sales (ch_rec) and the overall F-Score are significantly higher than those of the comparison samples. The behavior of equity issued to market options (issue) of the fraud companies is significantly higher than that of the comparison samples. However, the difference in Change in inventory (ch_inv), Percentage of soft assets (soft_assets), and Change in return on assets (ch_roa) is not significant.

3.2.3. Trend Change Prediction of M-Score and F-Score.

The author assumes that the year of the disclosure of the fraud is t, the year before the disclosure of the fraud is t-1, the two years before the disclosure of the fraud is t-2, (t-3, t-4 and so on), and the year after the disclosure of the fraud is t+1 (t+2, t+3 and so on), calculate the average value of M-Score and F-Score for each year of the fraud sample and the matching sample respectively to find the trend relationship between the years.

3.2.3.1. Trend Change Prediction of M-Score

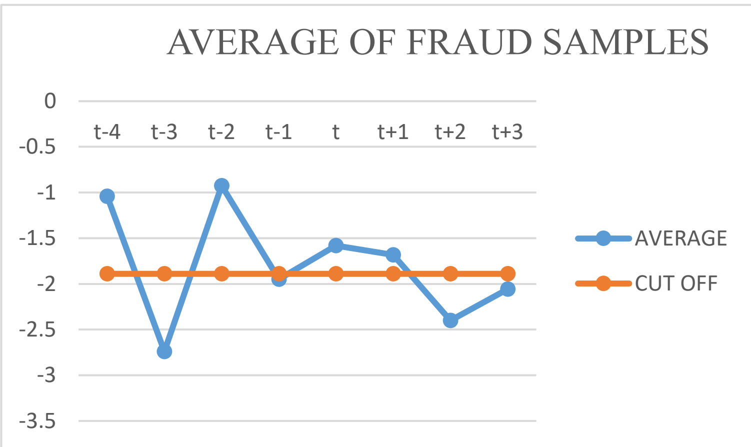

Figure 2: Average M-score of fraud samples around misstated years.

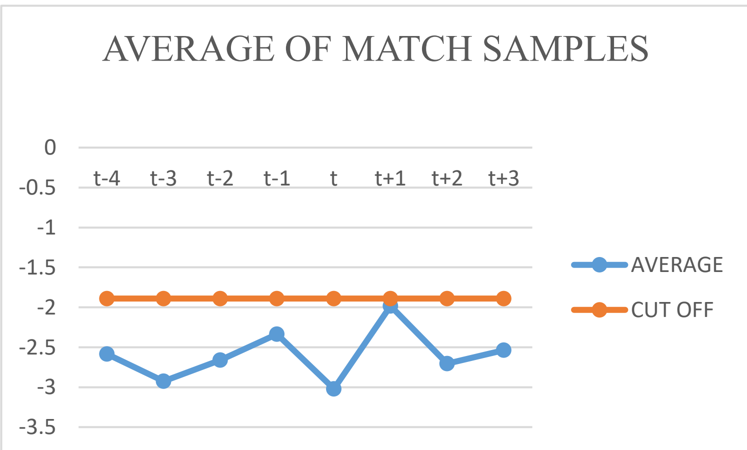

Figure 3: Average M-score of matched samples around misstated years.

As shown in Figure 2, the mean value of M-Score of the sample fluctuates up and down around the cutoff line [6], and the wave division. The range is relatively large. In the year when the fraud was disclosed, there was no significant mutation compared with other years, and there was a certain decline in the two years after the fraud was exposed. For the control sample, as shown in Figure 3, its

DOI: 10.54254/2754-1169/20/20230177

mean mainly fluctuates in a small range below the cutoff line, which is relatively stable compared with the fraudulent sample.

From the data, it can be concluded that M-Score does not distinguish significantly between the year of fraud disclosure and the year before the disclosure of fraud, but the large and unstable fluctuations between years are helpful to the trend prediction of fraudulent companies.

3.2.3.2. Change Trend of F-Score

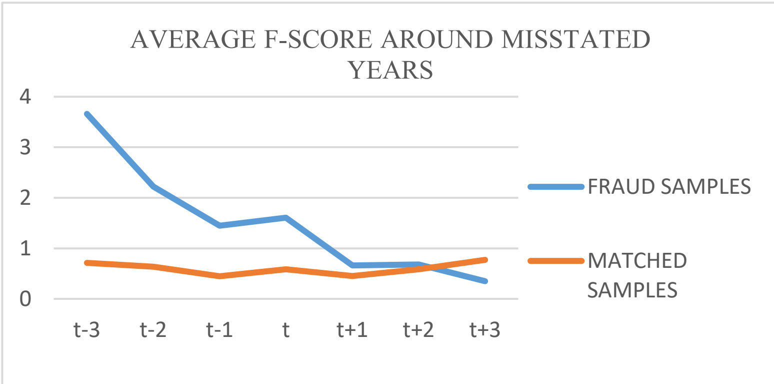

Figure 4: Average F-score around misstated years.

As shown in Figure 4, the average F-Score of fraudulent samples is higher than normal several years before the fraud is discovered. Always above normal risk [7]. It declined immediately in the second year after being reported for fraud and remained at a low-risk level for subsequent years. For the comparative samples, their F-Score average remained at a normal low-risk level. Therefore, investors evaluate the F-score of Chinese stocks is higher than the normal level of that may have helped them identify the fraud sooner than when it was discovered.

Because some companies may be listed for less than three years before being found guilty of fraud, and some companies have been delisted in the year or the second year when they are found guilty of fraud, the number of companies (n) in our fraudulent samples is different each year, but the number of companies in matched sample is always the same as that in fraudulent samples, and corresponds to each other. As for the phenomenon that the average value of F-Score in t-3 years is relatively high, two of the five samples of fraudulent companies have F-Score values higher than 5, so the interference of individual abnormal data on the presentation of the overall trend cannot be excluded.

4. Conclusion

The aim of the present research was to examine whether M-Score model F-Score model can help investors identify the fraud of Chinese stocks listed in the U.S. sooner than when it was discovered. This paper mainly takes the companies which were punished by the SEC for financial fraud from 2010 to 2021 as the observation samples. A total of 15 companies with fraud were selected as a comprehensive sample, while 15 Chinese companies listed in the United States that did not commit fraud in the same year were selected to match them (including those listed in Hong Kong as a supplement). The matching principle is that a fraudulent company corresponds to a non-fraudulent company with a similar market value in the same industry and selects data from the financial statements for the same year. We test the data of these samples through the existing financial fraud prediction model. It is hoped to verify the effectiveness of the M-Score model and F-Score model in predicting the misstatement risk of these companies.

Firstly, we conduct a student's t-test on two sets of data respectively, and the results show that both have a good ability to predict fraud for Chinese companies listed in the United States. We further compare and test the differences between the financial fraudulent samples and the comparison samples in the dimensions of each variable in the M-Score and F-Score models. We find that there are significant differences between the M-Score variables of the fraud sample and the comparison sample. The results of the difference between each variable are similar to those of Beneish [6].

Based on the verification of the above two kinds of validity, we draw the trend chart of the average M-Score and F-Score of the fraudulent samples from the three years before the misstatement year to the three years after the misstatement year and use the trend chart of the matched samples as a comparison. The trend of M-Score shows that for the counterfeiters, their M-Score is higher than the average non-manipulator [6] in most years, while the value of matched samples is generally lower than this level. Although the M-Score of the sample of fraudulent companies is not significant in the trend of changes from year to year, their huge fluctuations across years are significant relative to the matched sample, which is also of some help in identifying fraudulent companies. The trend chart of F-Score shows that the average F-Score of the fraudulent samples is higher than the normal value several years before the fraud is found and decreases immediately in the second year after the fraud is reported and remains at a low-risk level in the following years. However, the average F-Score of the comparison sample always remains at a low value. This is helpful for investors to warn of financial fraud by comparing M-Score and F-Score of these companies in previous years.

Therefore, investors can not only compare the changing trend or stable trend of listed companies M-Score and F-Score in previous years, but also compare them with companies in the same industry to determine whether the company is suspected of fraud. In addition, for a single year's financial results, investors can determine whether the company is at risk of misstatement based on whether their M-Score or F-Score is above their respective averages.

The limitation of this study is that the total number of Chinese companies is not large enough, and under the condition of having no missing financial statement data, we can only collect 15 companies with financial fraud. This may lead to relatively large sampling errors and insufficient reliability of the results. Consequently, it may be necessary to expand the sample size with more subsequent cases to repeatedly test our conclusions.

Acknowledgements

Tingyue Xu and Jingyi Liu contributed equally to this work and should be considered co-first authors.

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