Proceedings of the 2nd International Conference on Financial Technology and Business Analysis
DOI: 10.54254/2754-1169/92/20231274

Financial Statement Fraud Detection

- Applicable of Dechow F-score in China

Leyan Zeng[1,a,*], Qinzi Zhang[2], Miaohan Zhou[3]

[1]School of Economics and Management, Xiamen University, Xiamen, 361000, China
[2]Queen Anne's School, Reading, Britain, RG4 6DX, UK
[3]Weatherhead School of Management, Case Western Reserve University, Cleveland, Ohio, US, 44106, US
a. ACC2109054@xmu.edu.my, b. qinzizhang06@gmail.com, c. mxz721@case.edu
**corresponding author*

Abstract: This study focuses on the effectiveness of the Dechow F-SCORE model in monitoring financial fraud in the Chinese financial market. At the same time, the research also aims to thoroughly evaluate the advantages and deficiencies of the F-SCORE model. To implement research, six pairs of listed companies have been selected from different industries, and each company includes a company that has been involved in financial fraud cases and a company that has not had financial fraud. The annual report data of these companies conducted a comprehensive analysis in the vertical and horizontal directions. However, the results of the study show that when the F-SCORE model is applied to compare the financial fraud of these companies, the results are not noticeable. The results of the data analysis show that the F-SCORE model does not seem to detect financial fraud in Chinese-listed companies effectively. The conclusion of this study pointed out that the application of the F-SCORE model in Chinese listed companies is limited, and it may require more improvement and customization to adapt to the exceptional circumstances of the Chinese financial market. This also emphasizes that financial fraud monitoring involves various methods and tools to meet the needs of different regions and markets.

Keywords: Dechow F-score Model, mornting financial fraud, Chinese Financial Market

1. Introduction

1.1. Background

Does the F-score model apply to monitoring financial fraud in Chinese companies? Financial fraud seems to be increasingly moving away from the fringe market activities of the financial sector and becoming a pervasive type of behavior across the industry. The aftermath of the financial crisis of 2007–2008 revealed many scandals in which financial market participants infected the markets with fraudulent information to gain personal advantage [1].

In recent years, the increasing prevalence of financial fraud has emerged as a significant threat to companies operating in a challenging external environment. According to statistics, the number of financial fraud cases disclosed on the official website of the China Securities Regulatory Commission

DOI: 10.54254/2754-1169/92/20231274

(CSRC) has been escalating since 2000, with both the frequency and magnitude of fraudulent activities showing a marked increase. By April 2023, the total number of CSRC penalties in 2023 has reached 34 [2]. Figure 1 below shows how the number of CSRC punishments has changed from 2010-2020.

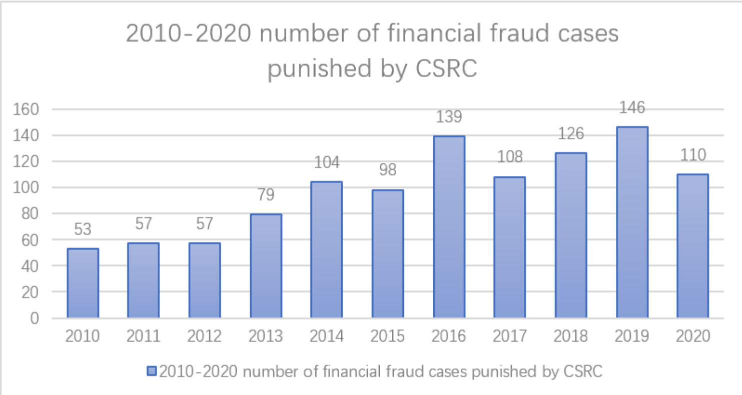

Figure 1: 2010-2020 number of financial fraud cases punished by CSRC[3]

The frequent occurrence of financial fraud hinders the healthy and sustainable development of companies, seriously harms the interests of investors, and affects the orderly operation of the market. Therefore, it is imperative to identify and prevent financial fraud effectively. Patricia Dechow et al. (2011) developed the F-score model to detect whether a firm has committed financial fraud. However, only some empirical articles in China demonstrate the applicability of this model in China. Therefore, this study is innovative in landing the F-score in China.

1.2. Research Design

In this paper, the F-score model is used to detect the company's economic operation to determine whether there is financial fraud. Data collection is conducted by selecting six pairs of public companies; one company in each team has committed financial fraud while the other has not. The selection criteria are based on the companies' size, growth, and industry. The pairs include Yihua Lifestyle and Sleemon, Kangmei Pharmaceutical and Yunnan Baiyao, ZONECO and Guolian Aquatic Products, Lonkey Industrial and Shenma Industrial, Tempus Hold and China Tourism Group Duty-Free Corporation Limited, as well as Kangde Xin Composite Material Group and Huadian Energy.

The F-score model is applied to calculate the financial metrics for each pair of companies to identify companies likely to manipulate earnings, and the data are from the disclosures released by the companies - annual reports. The model variables measure evidence of manipulation and managers' predisposition/opportunity to manipulate.

The variables include change in non-cash net operating assets (rsst_acc), change in receivables (ch_rec), change in inventory (ch_inv), percentage soft assets (soft_assets), change in cash sales (ch_cs), change in return on assets (ch_roa), and debt or equity issuance (issue). The predicted value is calculated using the formula: Predicted 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. A higher predicted value is associated with a higher probability of manipulation. The predicted value is then converted to a probability of manipulation using the logistic function = e^Predicted value/(1 + e^Predicted value) where e = 2.71828183. The F-Score is computed by dividing by the unconditional probability of manipulation (0.0037). F > 1 indicates "above normal" risk, F > 1.85 indicates "substantial" risk and F > 2.45 indicates "high" risk [4].

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There are two types of analysis of data: vertical and horizontal comparisons. The vertical comparison involves comparing a company's financial metrics before and after the occurrence of fraud. The horizontal comparison consists of comparing the companies with and without financial fraud to identify common factors that may contribute to fraudulent behavior.

The research aims to answer the question of whether the F-score model is effective in identifying financial fraud in Chinese public companies. A conclusion will be drawn based on the results of the analysis.

2. Data Collection and Analysis

2.1. Data Collection

In this paper, a total of 12 companies from 6 different industries are selected. Two companies from the same industry, one a fraud company and the other a non-fraud company are compared to conclude. Table 1 shows the basic data of these 12 companies for calculation.

Table 1: The basic data of 12 companies for calculation

Year	Total asset	Stockholders' equity	Preferred stock	Cash & equivalents	Receivable	Inventory	PPE	Sales	Net income
Chemical Industry									
Lonkey (fraud)									
2015	3,529,944,128.13	1,101,485,149.15	0.00	292,261,635.26	1,307,970,518.53	533,673,624.37	446,646,335.86	7,570,424,103.48	29,670,159.19
2016	4,170,269,340.96	1,785,077,271.57	0.00	309,863,448.71	1,756,363,128.65	502,899,355.26	463,789,923.50	9,849,073,706.86	38,992,067.98
2017	4,812,637,948.05	1,840,000,601.01	0.00	448,970,646.73	2,241,185,692.49	349,750,612.25	437,682,212.73	11,810,972,034.87	33,799,643.80
2018*	7,718,807,847.17	2,239,054,885.49	0.00	888,037,718.23	3,136,236,025.98	1,358,729,840.90	569,126,984.92	13,249,116,773.72	86,351,828.55
2019	8,892,656,755.31	1,904,291,758.32	0.00	1,032,174,833.50	3,445,511,412.84	1,377,196,834.03	587,386,026.08	12,397,507,679.81	78,513,101.26
Shenma									
2015	8,198,667,015.53	2,714,927,004.09	0.00	1,177,143,080.92	339,607,394.26	761,056,056.19	2,331,820,796.58	8,088,987,117.16	68,101,145.67
2016	9,856,295,325.45	2,838,139,229.22	0.00	2,277,025,749.83	407,822,684.53	602,263,595.68	2,506,820,204.37	10,040,256,145.06	105,642,095.94
2017	9,931,820,471.70	2,985,778,237.96	0.00	2,089,344,524.97	482,989,387.70	654,862,835.68	2,517,061,627.46	10,684,740,403.81	130,781,770.74
2018	10,964,581,345.23	4,011,241,941.52	0.00	1,836,584,338.28	384,101,196.73	1,005,043,769.78	2,661,805,332.56	11,153,158,281.97	963,743,703.56
2019	13,904,229,595.26	4,246,657,738.38	0.00	4,122,839,996.24	356,797,610.54	1,182,496,061.98	2,554,099,604.13	13,022,184,279.29	505,969,408.35
Fishery Industry									
Zoneco (fraud)									
2013	5,315,695,183.95	2,441,238,687.56	0.00	461,773,909.54	180,141,567.07	2,684,352,170.48	842,002,821.68	2,620,857,768.13	97,302,825.67
2014	4,878,243,239.41	1,156,556,599.81	0.00	595,861,445.15	201,939,812.71	1,706,755,623.73	1,291,095,375.49	2,662,211,458.16	-1,195,217,176.26
2015	4,485,387,128.18	908,185,707.69	0.00	579,527,692.27	254,954,879.79	1,543,400,986.71	1,247,176,273.58	2,726,780,243.72	-245,439,032.49
2016*	4,474,231,573.63	1,091,720,471.39	0.00	581,445,548.47	348,773,194.38	1,751,354,335.82	1,091,530,286.76	3,052,101,909.49	75,714,518.16
2017	3,944,015,805.83	403,188,936.15	0.00	494,113,721.93	436,687,855.30	1,209,170,806.50	1,043,812,012.17	3,205,845,988.90	-725,767,449.55

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Table 1: (continued).

Guo Lian									
2013	2,545,242,077.66	1,609,151,518.74	0.00	2,213,827,410.03	555,453,046.07	761,142,810.04	447,272,555.29	1,452,799,067.92	-225,507,725.19
2014	2,749,020,949.40	1,714,959,949.28	0.00	127,316,738.26	592,358,628.33	1,191,335,195.91	331,600,178.53	2,129,362,231.99	225,010,196.03
2015	2,596,059,001.82	1,733,172,732.56	0.00	104,743,680.70	633,073,485.29	1,086,639,482.20	321,402,563.39	2,070,469,926.65	22,765,728.30
2016	3,088,429,886.98	1,814,493,082.44	0.00	122,162,532.60	780,757,699.95	1,350,497,784.76	307,875,960.43	2,621,366,941.32	93,944,585.43
2017	3,932,109,674.26	1,948,892,124.00	0.00	209,097,863.26	745,757,061.77	2,034,812,969.21	375,147,357.08	4,095,806,660.34	144,132,610.64
Household Industry									
Yihua Lifestyle (fraud)									
2013	8,625,244,226.56	4,671,644,729.85	0.00	1,433,888,095.58	925,302,820.73	1,392,907,540.21	2,428,263,700.30	4,090,954,666.47	410,039,720.87
2014	10,249,656,087.50	6,378,947,434.99	0.00	2,220,575,789.06	1,177,933,586.42	1,763,680,149.61	2,620,498,380.87	4,426,628,727.81	527,295,036.29
2015	12,724,651,376.20	6,522,434,660.73	0.00	3,425,544,828.49	1,237,772,882.92	1,980,901,511.29	2,734,856,948.17	4,591,667,555.02	610,868,526.96
2016*	15,975,016,220.43	6,872,777,255.89	0.00	3,552,073,045.82	1,657,763,590.71	2,677,206,989.33	3,770,485,628.77	5,700,168,822.11	707,812,446.11
2017	16,701,463,828.25	7,912,029,190.15	0.00	4,229,034,586.32	1,828,907,187.47	2,791,238,128.22	3,936,669,277.11	8,021,563,711.14	748,059,461.86
Sleemon									
2013	1,509,327,415.41	1,097,041,367.52	0.00	280,524,480.54	242,965,108.42	138,973,083.06	222,136,000.72	947,114,516.76	97,588,348.25
2014	1,987,729,467.47	1,149,268,431.04	0.00	300,209,536.04	312,278,867.37	207,024,138.64	716,074,696.72	1,290,552,950.05	93,177,063.52
2015	823,561,802.97	1,339,665,039.51	0.00	236,710,288.97	528,854,973.08	323,603,159.77	823,561,802.97	1,687,437,125.87	190,142,986.89
2016	4,376,498,724.20	2,416,920,225.99	0.00	840,599,874.05	682,775,539.09	519,142,963.17	1,106,933,462.10	2,217,115,498.38	203,480,447.91
2017	5,787,951,839.27	2,745,118,454.82	0.00	1,048,702,921.47	1,031,909,627.99	786,706,606.85	1,108,803,207.72	3,187,357,907.81	282,371,466.47
Traditional Chinese Medicine Industry									
Kangmei (fraud)									
2013	22,251,388,975.04	12,030,387,620.22	0.00	8,497,052,709.39	1,705,348,741.09	3,785,913,720.97	3,848,840,184.00	13,358,728,517.00	1,880,413,503.51
2014	27,879,317,009.31	16,718,728,993.18	0.00	9,985,269,214.29	2,230,048,156.86	7,368,655,747.82	4,310,540,733.90	15,949,188,769.36	2,285,892,192.28
2015	38,105,229,314.85	18,838,440,063.36	2,967,700,000.00	15,818,341,613.15	2,550,400,592.90	9,794,699,683.97	4,790,347,557.15	18,066,827,952.30	2,756,456,305.57
2016*	54,823,896,576.81	29,383,127,034.14	0.00	27,325,140,365.21	3,095,183,749.30	12,619,374,963.24	5,919,649,265.52	21,642,324,070.28	3,336,759,125.48
2017	68,722,020,630.61	32,134,974,060.05	0.00	34,151,434,208.68	4,351,011,323.40	15,700,188,439.34	6,106,217,529.32	26,476,970,977.57	4,094,646,237.18
Yunnan Baiyao									
2013	12,880,915,675.82	9,028,790,168.90	0.00	2,082,951,549.60	536,467,059.54	4,757,358,043.23	1,269,767,136.49	15,814,790,880.81	2,321,453,787.17
2014	16,341,340,193.50	11,295,121,186.53	0.00	2,023,963,712.61	554,880,112.88	4,983,310,811.13	1,652,178,635.77	18,814,366,372.74	2,497,326,678.30
2015	19,290,940,366.09	13,527,805,322.34	0.00	2,649,769,547.43	1,057,735,076.07	5,625,005,009.07	1,640,213,179.39	20,738,126,205.08	2,755,581,110.10
2016	17,293,253,073.82	6,887,648,340.75	0.00	2,045,624,528.75	775,992,982.40	1,684,938,503.38	1,105,338,932.51	22,410,654,404.31	2,930,889,603.08
2017	27,702,530,540.34	18,142,917,483.07	0.00	2,666,326,412.14	1,233,810,339.12	8,663,278,462.90	1,745,371,710.46	24,314,614,044.21	3,132,534,170.45
High-tech Industry									
Kangdexin (fraud)									
2012	5,790,941,905.32	3,069,706,618.28	0.00	3,445,629,597.99	320,919,035.22	251,174,796.99	803,111,623.54	2,234,623,152.98	423,498,107.69

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Table 1: (continued).

2013	7,962,752,692.78	3,798,064,327.93	0.00	2,675,386,027.07	431,104,965.58	464,347,715.97	1,492,690,932.52	3,192,701,967.08	659,586,728.13
2014	10,876,503,651.97	4,826,640,154.28	0.00	4,192,943,122.78	1,770,341,668.21	494,991,977.74	3,403,469,019.69	5,208,091,770.62	1,000,216,276.11
2015*	18,562,061,263.46	9,350,302,165.64	0.00	10,096,144,186.33	2,838,062,302.45	531,743,002.72	3,466,758,362.86	7,560,816,182.51	1,434,022,372.76
2016	26,425,136,653.63	15,602,441,096.73	0.00	15,388,938,487.47	4,799,989,215.05	601,293,534.67	3,085,844,626.33	9,232,749,388.88	1,965,043,503.17
Huadian Energy									
2012	23,102,640,342.05	3,513,580,642.95	0.00	2,233,498,072.88	762,262,921.34	575,650,884.86	16,740,662,193.99	10,737,835,270.20	-448,885,208.16
2013	23,548,414,921.22	3,579,612,570.90	0.00	2,339,261,246.07	989,878,164.53	586,114,847.93	16,731,842,906.06	10,237,921,991.49	50,960,853.04
2014	23,815,689,052.37	3,802,488,050.77	0.00	883,676,662.97	1,400,720,593.67	637,934,480.17	16,414,628,107.89	9,829,383,541.64	158,081,806.78
2015	24,532,760,434.77	3,837,246,129.98	0.00	1,407,876,226.20	1,251,958,786.65	397,714,248.66	16,133,976,097.71	9,200,729,691.29	27,633,528.52
2016	25,453,958,216.40	4,098,916,087.47	0.00	1,096,500,932.35	979,485,102.22	321,761,252.16	17,538,195,665.10	8,633,017,069.39	172,230,915.19
Tourist Industry									
Tempushold (fraud)									
2016	4,715,815,849.62	1,714,235,472.06	0.00	718,595,846.77	411,988,504.24	0.00	282,223,464.36	1,280,243,711.13	195,383,306.98
2017	7,054,327,515.81	2,914,611,706.08	0.00	1,668,092,701.37	547,528,174.36	0.00	394,365,518.73	3,529,649,924.58	329,707,431.11
2018	9,253,541,748.81	3,207,471,299.39	0.00	1,360,689,970.00	836,556,023.36	0.00	422,355,936.19	4,886,107,475.54	172,238,187.05
2019*	6,519,405,740.80	1,342,762,494.19	0.00	555,042,722.91	371,404,013.40	0.00	315,970,017.46	3,296,995,453.66	-1,769,564,939.07
2020	4,792,506,227.70	156,981,331.02	0.00	86,936,763.48	139,648,500.00	0.00	322,147,821.62	545,075,298.38	-1,186,690,291.81
cdf									
2016	17,287,669,905.89	13,360,241,955.57	0.00	8,973,257,745.90	912,345,571.65	2,174,953,760.63	1,502,584,650.72	22,389,793,667.35	2,035,222,239.84
2017	20,932,207,413.07	15,011,278,388.59	0.00	11,484,245,018.59	946,475,387.21	3,217,815,021.48	1,425,746,325.10	28,282,286,665.72	2,934,550,221.64
2018	26,847,426,306.46	18,584,311,590.41	0.00	11,289,135,391.56	978,571,647.71	5,943,133,851.65	1,932,168,701.55	47,007,321,221.24	3,935,160,115.59
2019	30,687,255,888.76	22,310,356,325.04	0.00	11,905,950,444.67	800,081,884.72	8,059,771,737.67	1,631,763,135.49	47,966,495,033.74	5,414,712,071.36
2020	41,919,367,961.05	26,178,836,494.21	0.00	14,706,206,896.51	128,677,176.42	14,733,023,626.11	1,590,528,801.85	52,596,837,907.89	7,336,515,945.30

(* means the beginning of the fraud year)

In the selection of data, this paper takes the fraud year of the respective industry's fraud company as the primary line selects the financial information of the three years before the fraud and the two years at the time of the fraud, and uses this as the basis for calculating the seven variables and the F-score required for Dechow F-score.

The seven variables and their formulas required for this paper are as follows:

Table 2: Variables and formula required

Variable	Formula
rsst_acc	$(\Delta WC + \Delta NCO + \Delta FIN) /$ Average total assets
ch_rec	ΔAccounts Receivable / Average total assets
ch_inv	ΔInventory / Average total assets

DOI: 10.54254/2754-1169/92/20231274

Table 2: (continued).

soft_assets	(Total Asset) PP&E – Cash and Cash Equivalent)/Total Assets
ch_cs	(Sales –ΔReceivables)
ch_roa	Change in ratio of Net income/Average total assets
issue	

Predicted 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

F-score= $\frac{onee^{Predicted\ value}}{1+e^{Predicted\ value}}$,where e=2.71828183

In Table 2, all the variables for calculating the predicted value as well as the F-score and the formulae for the variables, are shown.

In the Dechow F-score study, it mentions that F > 1 indicates "above normal" risk, F > 1.85 indicates "substantial" risk and F > 2.45 indicates "high" risk [5]. If this study needs to prove that the Dechow F-score applies to China, it needs to show that the F-score of fraud companies in all industries is driven to increase before and after the fraud year, while the change in the F-score of non-fraud companies is not significant. Conversely, the Dechow F-score is not applicable to China.

2.2. Data Analysis

2.2.1. Comparison of F-score

Table 3: F-scores for 12 companies in different years

Year	F-score	Year	F-score	Year	F-score
Chemical Industry		**Fishery Industry**		**Household Industry**	
Lonkey		**Zoneco**		**Yihua Lifestyle**	
2015	0.0029040	2013	0.0020746	2013	0.0011648
2016	0.0034203	2014	0.0009860	2014	0.0049801
2017	0.0027067	2015	0.0009212	2015	0.0010852
2018*	0.0046828	2016*	0.0014112	2016*	0.0018979
2019	0.0022182	2017	0.0011240	2017	0.0013429
Shenma		**Guo Lian**		**Sleemon**	
2015	0.0011006	2013	0.0004361	2013	0.0040648
2016	0.0010795	2014	0.0135920	2014	0.0030756
2017	0.0011509	2015	0.0055562	2015	0.0020125
2018	0.0013333	2016	0.0031153	2016	0.0110910
2019	0.0011280	2017	0.0033995	2017	0.0161510
Traditional Chinese Medicine Industry		**High-tech Industry**		**Tourist Industry**	
Kangmei		**Kangdexin**		**Tempushold**	
2013	0.0011755	2012	0.0003622	2016	0.0028084
2014	0.0016813	2013	0.0032690	2017	0.0029217
2015	0.0009772	2014	0.0006088	2018	0.0029024
2016*	0.0029798	2015*	0.0005427	2019*	0.0014533
2017	0.0030942	2016	0.0009371	2020	0.0012148

DOI: 10.54254/2754-1169/92/20231274

Table 3: (continued).

Yunnan Baiyao		Huadian Energy		cdf	
2013	0.0019366	2012	0.0005218	2016	0.0007732
2014	0.0021335	2013	0.0005400	2017	0.0009002
2015	0.0025401	2014	0.0007023	2018	0.0016631
2016	0.0009385	2015	0.0006357	2019	0.0013950
2017	0.0052977	2016	0.0006235	2020	0.0018415

From Table 3, it can be seen that there is no obvious difference between the F-score of the fraud year and the F-score of the non-fraud year in the fraud company, and a suitable basic figure cannot be found to judge the severity of the risk. After comparing the F-score of the F-score of the fraud year and the F-score of the non-fraud year in the non-fraud company, it is not consistent with the expectation that the F-score is smoother.

2.2.2. Descriptive Analysis

Table 4: F-scores for 12 companies in different years

	Misstatement year			Non-misstatement year			Misstate-Nonmisstate	
variable	N	Mean	Median	N	Mean	Median	Diff. in mean	Diff. in median
rsst_acc	24	-0.038634	-0.032022	36	0.040167	0.023279	-0.078801	-0.055302
ch_rec	24	0.037592	0.039943	36	0.074998	-0.006179	-0.037406	0.046122
ch_inv	24	0.016330	0.024815	36	0.066885	0.063112	-0.050555	-0.038298
soft_assets	24	0.593065	0.556631	36	0.649493	0.623061	-0.056428	-0.066431
ch_cs	24	0.090729	0.113094	36	0.178042	0.113920	-0.087313	-0.000826
ch_roa	24	-0.032708	-0.004928	36	0.000205	0.005654	-0.032912	-0.010582
Issue	24	0.166667	0.000000	36	0.166667	0.000000	0.000000	0.000000
predict value	24	-6.418242	-6.547175	36	-6.105661	-6.434418	-0.312581	-0.112758
F-score	24	0.001908	0.001432	36	0.003912	0.001618	-0.002004	-0.000186

Table 4, by describing the median and mean of the F-score for all misstatement years and the F-score for all non-misstatement years, leads to the conclusion that the mean and median of the F-score for all non-misstatement years will be greater than that for all This is contrary to Dechow's findings [4]. This also suggests that the Dechow F-score may not be applicable to China.

2.2.3. Regression Analysis

In order to further verify the accuracy of the results obtained from the descriptive analysis, this study utilises regression analysis to determine the relationship between the F-score and whether the company is a fraud company as well as the fraud year.

This study was designed with the formula: $F - score_{it} = \beta_0 + \beta_1 \cdot Fraud_{it} + \beta_2 \cdot Post_{it} + \beta_3 \cdot Fraud \cdot Post_{it} + t$。Where Post indicates whether the fraud company is in the fraud year or not, Post=0 means that the fraud company is in the pre-fraud year, Post=1 means that the fraud company is in the fraud year. Fraud indicates whether the company is a fraud company or not. Fraud=0 means the company is non-fraud company, Fraud=1 means the company is fraud company. t in the formula represents the year.

DOI: 10.54254/2754-1169/92/20231274

Table 5: Data required for regression analysis

Company	Post	Fraud	F-score	Company	Post	Fraud	F-score
Fraud 1	0	1	0.002904	Non-fraud 1	0	0	0.001101
	0	1	0.003420		0	0	0.001080
	0	1	0.002707		0	0	0.001151
	1	1	0.004683		1	0	0.001333
	1	1	0.002218		1	0	0.001128
Fraud 2	0	1	0.002075	Non-fraud 2	0	0	0.000436
	0	1	0.000986		0	0	0.013592
	0	1	0.000921		0	0	0.005556
	1	1	0.001411		1	0	0.003115
	1	1	0.001124		1	0	0.003400
Fraud 3	0	1	0.001165	Non-fraud 3	0	0	0.004065
	0	1	0.004980		0	0	0.003076
	0	1	0.001085		0	0	0.002013
	1	1	0.001898		1	0	0.011091
	1	1	0.001343		1	0	0.016151
Fraud 4	0	1	0.001175	Non-fraud 4	0	0	0.001937
	0	1	0.001681		0	0	0.002134
	0	1	0.000977		0	0	0.002540
	1	1	0.002980		1	0	0.000938
	1	1	0.003094		1	0	0.005298
Fraud 5	0	1	0.000362	Non-fraud 5	0	0	0.000522
	0	1	0.003269		0	0	0.000540
	0	1	0.000609		0	0	0.000702
	1	1	0.000543		1	0	0.000636
	1	1	0.000937		1	0	0.000624
Fraud 6	0	1	0.002808	Non-fraud 6	0	0	0.000773
	0	1	0.002922		0	0	0.000900
	0	1	0.002902		0	0	0.001663
	1	1	0.001453		1	0	0.001395
	1	1	0.001215		1	0	0.001841

Table 5, is the database for the regression analysis. The Post value, Fraud value, and F-score of the fraud and non-fraud companies are filled in and brought into the formula according to the rules.

After regression analysis, the following values are obtained.

Table 6: Result of regression analysis

Variables	F-score
Post	0.00148
	-0.00107
Fraud	-0.000379
	-0.000959
Post·Fraud	-0.00162
	-0.00152

Table 6: (continued).

Constant	0.00243***
	-0.000678
Observations	60
R-squared	0.064
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Table 6 shows that the fraud*post corresponding F-score is -0.00162, which is relatively close to 0, indicating that F-score is not significant. Further analysis shows that the change in the F-score before and after the fraud is insignificant.

3. Conclusion

To sum up, this article introduces the F-score model, the F-score model applied to companies with financial fraud in China, and the horizontal and vertical comparison of the F-score model (vertical comparison involves comparing the company’s financial performance before and after the fraud occurs. Indicators and horizontal comparisons involve comparing firms with and without financial fraud).

From the Table 4 data analysis, it can be concluded that there is no significant difference between the F-score of the fraudulent company in the fraudulent year and the F-score in the non-fraudulent year. Therefore, the F-score cannot directly conclude whether the company has blatant fraud.

From the data analysis in Tables 3 and 6, it can be inferred that the value of the F-score is opposite to the data of the F-score, so there is a bold inference that the F-score is unsuitable for data analysis of Chinese companies.

Although the data analysis in this article believes that the F-score is unsuitable for financial or non-financial fraud analysis by Chinese companies, does the F-score have strong accuracy?

First, the F-score model is often more useful than accuracy, especially if the class is not evenly distributed. Accuracy works best if false positives and false negatives have similar costs. If the cost of false positives and false negatives differs, it is better to consider precision and recall.

Plus, systematic bias makes high precision and low accuracy possible. One of the problems with recall, precision, F-measure, and accuracy used in information retrieval is that they are prone to bias.

What are the advantages of the F-score? Microscopic precision or recall will result in a lower overall score. Therefore, it helps to balance the two metrics. If you choose the positive class as the class with fewer samples, the F-score can help to balance the metrics between positive/negative models.

In conclusion, the F-score has its advantages and disadvantages. However, it may not be suitable for analyzing Chinese companies regarding financial fraud. Therefore, it is challenging to determine if the F-score has fully utilized its potential in aiding the analysis of Chinese companies' financial fraud.

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