Detection of Fraud Statement Using Calculation Models M-Score and F-Score: Evidence from Chinese Companies Listed in the United States

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ABSTRACT
In recent years, the cases of financial fraud within China's listed companies in the U.S. have increased. Financial fraud usually fails to reflect the normal profitability of enterprises and harms the interests of small and medium investors, disturbing the normal operation of the market as a result. The goal of this study was to examine whether M-Score and F-Score models are fit for U.S.-listed Chinese Companies and to find clues to financial fraud of Chinese enterprises. To this end, we applied M-Score and F-Score models to 2 groups (14 samples) of companies from 5 different industries. There is a 13-year span between the earliest and latest allegations of financial fraud. The sample companies that have been caught in fraud were chosen to be the experimental group (EG) and the companies without committing fraud were selected to be the control group (CG). The findings suggest that M-Score model fits the U.S.-listed Chinese companies, while there is insufficient evidence to prove that F-Score model can be applied.

KEYWORDS: *Financial reporting fraud, Chinese companies listed in the U.S., Fraud detection models.*

1. Introduction

Xinhua News Agency recently released data showing that since 2020, 59 cases of financial fraud and other illegal acts of listed companies have been dealt with, accounting for 23% of information disclosure cases. And 21 suspected criminal cases have been transferred to public security organs [1].

Financial fraud refers to "any intentional or deliberate act to deprive another of property or money by guile, deception, or other unfair means" [2]. Financial fraud has the characteristics of a complex pattern, hidden technique and diversified motives. The main forms are forging and altering accounting records or vouchers; concealing or deleting transactions or matters; recording false transactions, deliberately using improper accounting policies, deliberately preparing financial reports in violation of accounting standards, etc.

In recent years, there have been more and more cases of financial fraud within China's listed companies in the U.S., among which Luckin coffee is the one we may be most familiar. Financial fraud not only has a great impact on the rights of shareholders but also seriously affects the judgment of decision-makers. It disturbs the normal operation of the market and fails to reflect the normal profitability of enterprises, as well as harms the interests of small and medium investors.

The purpose of the research is to first calculate the M-Score [3] and F-Score [4] of ten sets of companies during the period of the fraud year. Second, indicate the difference in M-Score and F-Score between companies committing fraud in financial reports and those (in the same industry and size) who did not commit fraud. Third, testify to the usefulness of M-Score and F-Score models in identifying fraud on financial reports. Fourth, suggest a tool for investors to identify financial fraud.

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2. Research design

2.1 Beneish M-Score

Eight-variable model designed to identify companies likely to manipulate earnings (Table 1)

Table 1 Calculation of M-Score variables

Variables	Numerator year	Denominator Year	Formula
Days Sales in Receivables Index (DSRI)	t	t-1	Receivables/Sales
Gross Margin Index (GMI)	t-1	t	(Sales-COGS)/Sales
Asset Quality Index (AQI)	t	t-1	1-((Current assets +PP&E, net)/Total assets)
Sales Growth Index (SGI)	t	t-1	Sales
Depreciation Index (DEPI)	t-1	t	Depreciation/(Depreciation +PPE, net)
SG&A Expense Index (SAI)	t	t-1	SG&A/sales
Leverage Index (LVGI)	t	t-1	(LT debt + Current LIabilities)/Total assets
Days Sales in Receivables Index (DSRI)	t	NA	Total accruals/Total assets

M-Score=-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

Higher M is associated with a higher probability of manipulation. M-Score value higher than -2.22 indicates a potential manipulator (higher M than average non-manipulator). Beneish also suggests that an M-Score value higher than -1.89 is a cutoff to determine whether the error is due to a manipulator.

2.2 Dechow F-Score

Seven-variable model designed to identify companies likely to manipulate earnings (Table 2)

Table 2 Calculation of F-Score

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

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

Convert predicted value to probability of manipulation using logistic function:

= ePredicted value/ (1 + ePredicted value) where e = 2.71828183

Compute F-Score by dividing by the unconditional probability of manipulation (0.0037)

A higher predicted value means associated with a higher probability of manipulation. An F-Score value higher than 1 indicates “above normal risk” and an F-Score higher than 2.45 indicates “high risk”.

2.3 Procedure

a. Collect the financial statement from annual reports companies disclose to SEC
b. record the item used to calculate M-Score and F-Score variables
c. Calculate M-Score and F-Score variables
d. Analysis and evaluation result

3. Sample selection

The subjects of this study are seven Chinese companies listed in the United States in recent 5 -15 years (including delisted and listed), while the sample selection with the criteria used, namely:

Chinese companies were listed in the United States from 2005 to 2020 (including delisted and listed)[5]. 7 more companies that belonged to the same industry on a similar scale and type to are chosen to be the control group. The rule aims to minimize the difference in the mode of information disclosure caused by different industries.

The audited financial statements and annual reports from 2005 to 2020 published by the SEC, including the year of financial fraud or suspected financial fraud and its adjacent years.

After evaluation, the seven companies we chose as experimental group are (Table 3):

(1) **RINO INTERNATIONAL CORPORATION** is a technology-based company that engages in environmental protection and remediation in China. Its main business is to design, sell and maintain wastewater treatment and exhaust emission desulphurization equipment for China's steel and iron industries. The company was accused of overstating revenue in financial reports, diverting money for personal use by the CEO and chairman couples and providing Fillings containing materially false and misleading statements and omissions in the period 2007-2010. The company was delisted by NASDAQ in the year 2010.

(2) **Universal Travel Group (UTG)** is a company offering online services including hotel reservations, air ticket booking, packaged travel, and air delivery services. In 2013, SEC made official charges against UTG including failing to disclose important data, failing to properly document cash transactions, and overstating revenue and profit. the price of stock dropped significantly after the exposure by Claucus Research Group. The company voluntarily delisted from NYSE in 2012 [6].

(3) **GOTU** is a B2C online education institution. Founded under the leadership of Chen Xiangdong in June 2014, it is a leading online education technology company in China, upgraded from "Learn from who". The team members mainly come from education and training institutions such as New Oriental and Internet companies such as Baidu, Alibaba, and Tencent. According to the financial report, the 2019 financial data is very bright, and the net profit surged 10 times. But on February 25th Grizzly, a short-selling firm, published a 50-page report on shorting from which he recounted several SINS: false accounting, inflated student numbers with false orders, and selling by old shareholders. Bottom line: the worst public online education company I've ever seen.

(4) **IQIYI** is a large-scale video website and a professional online video broadcasting platform, focusing on advertising revenue and member income. IQIYI was listed on NASDAQ on March 29, 2018. Wolfpack research is short, starting from the deferred income related to iqiyi VIP membership fee, questioning the fraud of revenue (membership fee receivable accounts for 49.8% of the revenue of 2019 annual report), and falsely increasing the revenue of membership fee from the joint member income recognition methods of credit card, jd.com, Xiaomi and operators.

(5) **QTT (Qutoutiao)** opened the sinking market with the mode of "making money by watching interesting headlines", with entertainment and life information as the main content. On the evening of September 14, 2018, interesting headlines were officially listed on the NASDAQ Exchange. Wolfpack research is short. In 2018, 74% of the sales and 77% of the cash balance were false, and nearly 50% of the advertising came from undisclosed related parties. Among the 50000 advertising samples it tested, Wolfpack research found that four companies accounted for 69.7% of the total advertising flow of interesting headlines.

(6) **TAL** was a technology education company that mainly provided after-school tutoring education in K-12 industry. In 2018 June, Muddy Water Research claimed that TAL had overstated net income by more than 43% over the past two fiscal years. There are 2 main arguments in the reports of Muddy Water Research: exaggerating profits both in a related transaction and an acquisition. Then in 2020, an internal employee exposed that the company has misstated more than $100 million in revenue. The company admitted to the financial fraud but did not announce the specific amount.

(7) **KANDI** is mainly engaged in investment, R&D, production, marketing, and other related businesses of pure electric vehicles. In 2020, Hinderburg Research claimed that Kandi has falsified its financial report that the company had undisclosed significant related parties who contributed 64% of Kandi's last twelve months (LTM) sales.

4. Analysis and result

4.1 Analysis of M-Score of 7 sets of companies

In the first experiment group--RINO International Corporation and Subsidiaries vs. SINOPEC Shanghai Petrochemical Company Limited. The RINO International Corporation, the financial fraud one, had an m-Score that is all below -2.22 from 2006 to 2008, which means that there is the potential for manipulation. In 2009, it had an m-score of -3.1418 which was a normal Score. The control company- SINOPEC Shanghai Petrochemical Company Limited had all normal numbers which were all below -2.22.

In the second group, Universal Travel Group vs. Ctrip.com International LTD. The experiment company Universal Travel Group has all m-Score above -2.22 from 2006 to 2009, which means that the company had a potential for manipulation from 2006 to 2009. Interestingly, the control company Ctrip.com International LTD. had an m-Score above -2.22 in 2006 and 2007 but have normal Scores in 2008 and 2009. These Scores show that the Ctrip.com International LTD had the potential for manipulation from 2006 to 2007.

The third group KANDI vs. NIO. The KANDI company had an m-Score that is above -2.22 from 2017 to 2018 and above -2.22 from 2019 to 2020. It indicates that KANDI was risky for investors from 2017 to 2018 and has no risk from 2019 to 2020. The compared NIO had an abnormal m-Score from 2017 to 2019 but have a normal m-Score in 2020. It shows that the company is risky from 2017 to 2019, but it was normal in 2020.

In the fourth group TAL vs. DAO. The suspicious company TAL had a normal m-Score from 2017 to 2020. However, the control company DAO had an abnormal m-Score in 2020. This table shows that the suspicious company Tal had no potential for manipulation, but the control company DAO had the potential of making financial fraud in 2020.

In the fifth group IQIYI vs. BILIBILI. Iqiyi had an m-Score below -2.22 from 2018 to 2020. It illustrates that Iqiyi has a low potential for manipulating their performance. The control company had an abnormal m-Score of -2.0146, which shows the possibility of faking financial performance.

In the sixth group QTT vs. WEIBO, the suspicious company QTT had two abnormal MScore above -2.22. in 2017 and 2018 and M-Score below -2.22 in 2019 and 2020. The control company WEIBO had an abnormal M Score in 2018 which shows the possibility of financial fraud in 2018.

In the last group GOTU vs. YQ. The suspicious company had M-Score above -2.22 in 2018. This means that it had the potential of manipulation in 2018 and 2021 and has a low risk from 2019 to 2020. The compared company YQ has a normal m-Score from 2019 to 2020 but has an abnormal m-Score in 2021.

12 out of 22 fraud companies have an M-Score value higher than -2.2 while 6 out of 22 control companies do. (Table 3&4)

Table 3 Detailed M-Score result

RINO INTERNATIONAL CORPORATION AND SUBSIDIARIES & SINOPEC SHANGHAI PETROCHEMICAL COMPANY LIMITED																		
	DSRI		GIM		AQI		SGI		DEPI		SAI		LVGI		TATA		MScore	
2006	1.5455	0.0264	0.0803	0.0606	-0.7641	0.2196	2.9568	1.1010	0.0083	0.1123	0.1899	0.0114	1.2124	0.3019	-0.0552	-0.0307	-1.7332	-3.9445
2007	1.9564	0.0347	0.0854	0.0256	-1.8027	0.1274	5.8931	1.0935	0.0076	0.1093	1.3698	0.0100	0.6484	0.3248	0.0752	0.0049	1.4382	-3.8400
2008	0.8466	0.0096	0.2186	0.0445	-0.7910	0.3373	2.1983	1.0885	0.0412	0.1143	0.2329	0.0085	0.4381	0.4613	0.1165	-1.3074	-1.9380	-9.9569
2009	0.4180	0.0095	0.2820	-0.1612	-1.1189	0.1269	1.3825	0.8577	0.0509	0.0976	0.1216	0.0075	0.1286	0.5306	0.0942	-0.0566	-3.1418	-4.5282
Universal Travel Group & CTRIP.COM INTERNATIONAL, LTD																		
	DSRI		GIM		AQI		SGI		DEPI		SAI		LVGI		TATA		MScore	
2006	0.2462	0.2614	-0.9867	3.6259	0.3392	0.4901	0.9664	0.1428	-1.3328	0.2462	0.2614	-0.9867	3.6259	0.3392	0.4901	0.9664	0.1428	-1.3328
2007	0.6692	0.1223	-1.1655	4.4234	0.2222	0.3225	1.0931	0.0515	-0.8314	0.6692	0.1223	-1.1655	4.4234	0.2222	0.3225	1.0931	0.0515	-0.8314
2008	0.2044	0.1925	-0.1884	1.7329	0.2777	0.1037	0.1679	0.1610	-2.3680	0.2044	0.1925	-0.1884	1.7329	0.2777	0.1037	0.1679	0.1610	-2.3680
2009	0.1899	0.3417	-0.5269	1.2751	0.0133	0.1069	0.1269	-0.0890	-4.0351	0.1899	0.3417	-0.5269	1.2751	0.0133	0.1069	0.1269	-0.0890	-4.0351
KANDI & NIO																		
	DSRI		GIM		AQI		SGI		DEPI		SAI		LVGI		TATA		MScore	
2017	0.2656	0.0000	2.3468	0.0000	0.4307	0.0000	0.7939	0.0000	0.2898	0.0000	-0.0988	0.0000	0.4913	0.0000	0.0022	0.0000	-2.5745	
2018	0.3334	0.0000	1.7011	0.0000	0.4310	0.0000	1.0937	0.0000	0.0553	0.0000	-0.1148	0.0000	0.4739	0.0000	-0.0411	0.0000	-2.8068	
2019	0.5441	0.2697	1.5075	1.3145	0.3704	0.4517	1.2072	1.5608	0.0524	0.0735	-0.1629	-1.0875	0.4131	1.3307	0.0587	0.5833	-2.1434	0.1664
2020	0.2840	0.1532	3.1988	0.9713	-0.0035	-2.7464	0.5667	2.2168	0.1114	0.1549	-0.1448	-0.5362	0.1847	0.4169	0.0802	-0.0484	-2.0330	-3.5713
TAL & DAO																		
	DSRI		GIM		AQI		SGI		DEPI		SAI		LVGI		TATA		MScore	
2017	0.0055		0.8854		0.0339		1.6826		0.0991		-0.6279		0.8405		-0.1457		-4.0346	
2018	0.0031		0.9128		-0.0439		1.6442		0.0970		-0.6024		0.7427		-0.1606		-4.1056	
2019	0.0019	0.2569	1.0134	1.0202	0.3342	-2.1053	1.4944	1.6704	0.1396	0.1945	-0.6202	-0.8912	0.3875	2.6987	0.0456	-0.1098	-3.0538	-3.2074
2020	0.0014	0.2198	1.1387	0.6626	0.2336	0.0298	1.2771	2.5899	0.1645	0.1605	-0.6429	-2.3184	0.5538	1.7782	-0.1765	-0.6916	-3.9969	-1.2846
IQIYI & BILIBILI																		
	DSRI		GIM		AQI		SGI		DEPI		SAI		LVGI		TATA		MScore	
2016																		
2017		0.7530		-2.1429		0.3265		4.9503		1.2254		0.1888		1.3884		-0.2004		-2.0146
2018	0.8989	0.4936	0.0058	1.0738	0.5203	0.3380	1.3773	1.6021	0.9739	1.0015	1.0836	1.2686	0.9538	0.7813	-0.2502	-0.1344	-4.1282	-3.2409
2019	1.0822	0.9892	1.8373	1.1800	0.4921	0.3014	1.1387	1.6111	1.0339	0.8929	1.0828	1.0421	1.3401	1.5754	-0.3075	-0.1028	-3.6042	-2.8207
2020	0.8998	1.1298	-0.7606	0.7419	0.4877	0.3086	1.0989	1.8987	0.9957	0.9843	0.9670	1.4092	1.0341	1.3306	-0.0331	-0.1647	-3.7812	-2.9255
QTT & WEIBO																		
	DSRI		GIM		AQI		SGI		DEPI		SAI		LVGI		TATA		MScore	
2017	0.4354	0.8358	1.0282	0.9249	0.0120	0.1872	9.3580	1.7537	0.0000	1.2172	0.9881	0.9565	0.4750	1.9865	-0.4762	-0.0706	1.9022	-2.9472
2018	0.8068	1.4521	1.0224	0.9529	0.0409	0.2321	5.5984	1.4943	0.2233	1.0294	1.3902	1.2026	0.6180	0.8678	-0.5508	0.0236	-1.5403	-1.8360
2019	1.4014	1.1126	1.1813	1.0301	0.0526	0.2314	1.8089	1.0282	1.6551	0.8821	0.7383	0.9469	2.6301	1.1204	-0.1152	-0.0180	-2.6279	-2.7737
2020	1.4760	1.2183	1.0326	0.9911	0.1290	0.2262	1.0177	0.9564	0.6645	0.9897	0.6910	1.0470	0.9965	1.0326	-0.0667	-0.0425	-2.6572	-2.8539
GOTU & YQ																		
	DSRI		GIM		AQI		SGI		DEPI		SAI		LVGI		TATA		MScore	
2017			0.0000						0.0000						1.8654			
2018	0.2784		0.1814	0.0000	-2.2816		4.0928		0.1549	0.0000	2.4227		3.5437		1.4128	0.3037	1.2394	
2019	0.1864	0.0482	0.1201	0.5074	-9.0444	0.3629	5.3275	1.3055	0.0084	0.1606	3.4332	3.9646	5.4349	0.4879	1.2127	0.5356	-3.1531	-5.3806
2020	0.0307	0.0172	0.2216	0.1801	-2.1476	-2.6928	3.3688	3.1872	0.0105	0.1318	3.3650	5.2537	1.4598	1.4444	0.8502	0.4247	-2.6958	-7.3146
2021	0.0000	0.0000	0.8171	0.3652	0.5298	0.5339	0.9210	1.6886	0.0708	0.4093	0.9968	2.0541	0.2006	0.2310	1.6668	1.6270	3.2829	2.4034

Table 4 M-Score statistical overview

M-score				
		Experimental Group	Control Group	
RINO	2006	-1.7332	-3.9445	XNYS:SHI
	2007	1.4382	-3.8400	
	2008	-1.9380	-9.9569	
	2009	-3.1418	-4.5282	
UTG	2006	0.1428	-1.3328	Ctrip
	2007	0.0515	-0.8314	
	2008	0.1610	-2.3680	
	2009	-0.0890	-4.0351	
KANDI	2019	-2.1434	0.1664	NIO
	2020	-2.0330	-3.5713	
TAL	2019	-3.0538	-3.2074	DAO
	2020	-3.9969	-1.2846	
IQIYI	2018	-4.1282	-3.2409	BILIBILI
	2019	-3.6042	-2.8207	
	2020	-3.7812	-2.9255	
QTT	2017	1.9022	-2.9472	WEIBO
	2018	-1.5403	-1.8360	
	2019	-2.6279	-2.7737	
	2020	-2.6572	-2.8539	
GOTU	2019	-3.1531	-5.3806	YQ
	2020	-2.6958	-7.3146	
	2021	3.2829	2.4034	
	higher than -2.2	12	6	

Table 5 Detailed F-Score result

RINO INTERNATIONAL CORPORATION AND SUBSIDIARIES & SINOPEC SHANGHAI PETROCHEMICAL COMPANY LIMITED																		
	rsst_acc		ch_rec		ch_inv		soft_assets		ch_cs		ch_roa		issue		Predictive value		Manipulation possibility	
2006	0.2120	-0.0167	0.3079	0.0177	-0.0470	0.1384	0.4501	0.4851	0.7859	0.1082								
2007	0.0904	-0.0001	0.3683	0.0190	0.0016	0.0361	1.0455	0.4884	7.5303	0.0931	0.0550	0.0252	1	1	-2.5576	-5.8141	0.0719	0.0036
2008	0.0260	-0.0093	0.3608	-0.0427	0.0113	-0.0246	1.0586	0.4751	1.2250	0.1217	-0.0087	0.1574	1	1	-3.6089	-6.1936	0.0264	0.0020
2009	0.6605	-0.0175	0.0243	0.0014	0.0223	0.0833	0.5948	0.5155	0.7620	-0.1600	0.0632	-0.1585	1	1	-5.0060	-5.6345	0.0067	0.0030
Universal Travel Group & CTRIP.COM INTERNATIONAL, LTD																		
	rsst_acc		ch_rec		ch_inv		soft_assets		ch_cs		ch_roa		issue		Predictive value		Manipulation possibility	
2006	-0.0209	0.0879	0.1199	0.0589	0.0000	0.0000	1.1403	0.3648	2.3797	1.5409								
2007	0.0869	0.1230	0.3212	0.0693	0.0000	0.0000	1.4471	0.4436	3.1005	0.5291	0.0129	0.0293	1	1	-2.6045	-5.6512	0.0689	0.0035
2008	0.3289	0.0023	0.0593	0.0058	0.0000	0.0000	0.8434	0.4886	0.9441	0.3537	-0.0976	-0.0332	1	1	-4.5332	-5.7893	0.0106	0.0031
2009	0.3102	0.1086	0.0818	0.0436	0.0000	0.0000	0.6517	0.6466	0.2412	0.2550	-0.2072	0.0090	1	1	-4.8889	-5.3537	0.0075	0.0047
KANDI & NIO																		
	rsst_acc		ch_rec		ch_inv		soft_assets		ch_cs		ch_roa		issue		Predictive value		Manipulation possibility	
2017	-0.0046		0.0046		0.0355		0.9615		0.0618		-0.0499		1		-4.8541		0.0077	
2018	-0.0188		-0.0003		0.0139		0.7722		-0.0036		0.0514		1		-5.3834		0.0046	
2019	0.0194	-0.6461	0.0673	0.0348	-0.0547	-0.0353	0.7992	0.5614	0.7850	0.7651	-0.0061	-0.2631	1	1	-5.0228	-5.8418	0.0065	0.0029
2020	0.4158	-0.1336	-0.0522	-0.0042	0.0001	0.0073	0.8560	0.2053	-0.3700	-0.1131	-0.0016	0.6776	1	1	-5.0346	-7.2159	0.0065	0.0007
TAL & DAO																		
	rsst_acc		ch_rec		ch_inv		soft_assets		ch_cs		ch_roa		issue		Predictive value		Manipulation possibility	
2017	0.2656		2.3468		0.4307		0.7939		0.2898		-0.0988		1		-5.6977		0.0035	
2018	0.3334	-3.8191	1.7011	0.6477	0.4310	0.0769	1.0937	0.9030	0.0553		-0.1148		1	1	-5.2846		0.0035	
2019	0.5441	1.0187	1.5075	-0.0099	0.3704	0.0384	1.2072	0.8995	0.0524	-0.0635	-0.1629	0.0495	1	1	-5.6405	-4.3153	0.0050	0.0036
2020	0.2840	-1.0652	3.1988	0.0401	-0.0035	0.0374	0.5667	0.6837	0.1114	0.4293	-0.1448	-0.5587	1	1	-5.6524	-5.6128	0.0033	0.0132
IQIYI & BILIBILI																		
	rsst_acc		ch_rec		ch_inv		soft_assets		ch_cs		ch_roa		issue		Predictive value		Manipulation possibility	
2017		0.7530		-2.1429		0.3265		4.9503		1.2254		0.1888						
2018	0.8860	0.4936	0.0169	1.0738	0.0000	0.3380	0.8614	1.6021		1.0015	-0.0515	1.2686	1	1		-4.8036		0.0081
2019	-0.2228	0.9892	0.0151	1.1800	0.0000	0.3014	0.8122	1.6111	0.1372	0.8929	0.0483	1.0421	1	1	-5.4161	-5.5197	0.0044	0.0040
2020	-0.1123	1.1298	-0.0008	0.7419	0.0000	0.3086	0.7238	1.8987	0.1269	0.9843	0.0719	1.4092	1	1	-5.5678	-5.0197	0.0038	0.0066
QTT & WEIBO																		
	rsst_acc		ch_rec		ch_inv		soft_assets		ch_cs		ch_roa		issue		Predictive value		Manipulation possibility	
2017	0.4354	0.8358	1.0282	0.9249	0.0120	0.1872	9.3580	1.7537	0.0000	1.2172	0.9881	0.9565	1	1				
2018	0.8068	1.4521	1.0224	0.9529	0.0409	0.2321	5.5984	1.4943	0.2233	1.0294	1.3902	1.2026	1	1	-4.7895	-5.3345	0.0082	0.0048
2019	1.4014	1.1126	1.1813	1.0301	0.0526	0.2314	1.8089	1.0282	1.6551	0.8821	0.7383	0.9469	1	1	-5.1075	-5.3209	0.0060	0.0049
2020	1.4760	1.2183	1.0326	0.9911	0.1290	0.2262	1.0177	0.9564	0.6645	0.9897	0.6910	1.0470	1	1	-5.7730	-5.3654	0.0031	0.0047
GOTU & YQ																		
	rsst_acc		ch_rec		ch_inv		soft_assets		ch_cs		ch_roa		issue		Predictive value		Manipulation possibility	
2017							-0.5979											
2018	0.0000		-0.2105		0.0000		0.1033	0.2044	5.1236		0.0000		1	1	-6.3134		0.0018	
2019	0.0000	0.0000	0.7538	-1.2882	0.0000	0.0000	0.2260	-0.6773	-16.8843	31.5714	0.0000	0.0000	1	1	-7.4058	-6.0494	0.0006	0.0024
2020	0.0000	0.0000	-0.1054	0.3587	0.0000	0.0000	0.4109	0.0680	18.5700	-28.5372	0.0000	0.0000	1	1	-3.1407	-10.7061	0.0415	0.0000
2021	0.0000	0.0000	-0.7340	-1.8967	0.0000	0.0000	0.9415	0.6874	77.3883	17.8645	0.0000	0.0000	1	1	6.3843	-7.2246	0.9983	0.0007

Table 6 F-Score predictive value statistical overview

Predictive value				
		Experimental Group	Control Group	
RINO	2007	-2.5576	-5.8141	XNYS:SHI
	2008	-3.6089	-6.1936	
	2009	-5.0060	-5.6345	
UTG	2007	-2.6045	-5.6512	Ctrip
	2008	-4.5332	-5.7893	
	2009	-4.8889	-5.3537	
KANDI	2019	-5.0228	-5.8418	NIO
	2020	-5.0346	-7.2159	
TAL	2019	-5.6405	-4.3153	DAO
	2020	-5.6524	-5.6128	
IQIYI	2019	-5.4161	-5.5197	BILIBILI
	2020	-5.5678	-5.0197	
QTT	2018	-4.7895	-5.3345	WEIBO
	2019	-5.1075	-5.3209	
	2020	-5.7730	-5.3654	
GOTU	2019	-7.4058	-6.0494	YQ
	2020	-3.1407	-10.7061	
	2021	6.3843	-7.2246	
	higer than 1	1	0	

Table 7 F-Score manipulation possibility statistical overview

manipulation possibility				
		Experimental Group	Control Group	
RINO	2007	0.0719	0.0036	XNYS:SHI
	2008	0.0264	0.0020	
	2009	0.0067	0.0030	
UTG	2007	0.0689	0.0035	Ctrip
	2008	0.0106	0.0031	
	2009	0.0075	0.0047	
KANDI	2019	0.0065	0.0029	NIO
	2020	0.0065	0.0007	
TAL	2019	0.0050	0.0036	DAO
	2020	0.0033	0.0132	
IQIYI	2019	0.0044	0.0040	BILIBILI
	2020	0.0038	0.0066	
QTT	2018	0.0082	0.0048	WEIBO
	2019	0.0060	0.0049	
	2020	0.0031	0.0047	
GOTU	2019	0.0006	0.0024	YQ
	2020	0.0415	0.0000	
	2021	0.9983	0.0007	
	higher than 0.1	1	0	

Analysis of M-Score of 7 sets of companies

RINO has shown a higher predictive value and manipulation possibility than SINOPEC SHANGHAI PETROCHEMICAL COMPANY, but none of values reach the degree of high risk of manipulation.

The second group, UGT shows a higher predictive value than CTRIP. But the possibility in both companies is lower than 1, and none are recognized to have significant fraud suspects.

For KANDI and NIO, KANDI, the fraud company, has a similar value to NIO, the control company. The same pattern is found in three other groups: TAL&DAO, IQIYI & BILIBILI and QTT & WEIBO. One difference worth noticing is in the last group GOTY&YQ. In the year 2020, the predictive value of GOTU is significantly higher than YQ, concerning values of -3.14 and -10.7. And in 2021, the predictive value of GOTU is 6.38 with a manipulation possibility of 100%, which is the most significant fraud detection ever encountered in the research.

Only data of one year of one company shows significant possibility of manipulation.

4.2 T-test analysis

T-test invented by William Sealy Gosset [7] is used to determine the statistical difference between samples. To find out whether there are significant differences in M-Score, F-Score predictive value and F-Score possibility between experimental(fraud) and control groups, a T-test is run using SPSS program. The data are only collected for T-test when both control group and experimental group have valid Scores in that particular year. Since F-Score and M-Score's calculation involves changes in financial reports, fraud on financial reports is likely to have influenced the figure on previous years' reports and next year's report. Thus, the year of data taken is one year before fraud and the fraud year for most companies. these companies have just been in the market for less than five years. But for RINO and UTG, years of data collected are one year before fraud, fraud year and one year after fraud. And to prove that data collected is valid for T-test. Test and variables proving for normal distribution including median, mean, standard deviation, skewness, kurtosis, and S-W test are calculated and checked.

Since the data is relatively small, S-W test is used to indicate the normality. For M-Score, both data of experimental group (EG) and control group (CG) show a possibility low than 0.1 which is insufficient to reject the null hypothesis. M-Score value is valid for normal distribution. However, for F-Score, the S-W Score is about 0.5 suggesting that data may not fit normal distribution (Table 8). So, a normal distribution histogram is also drawn to assist the judgment. The graph does not have perfect symmetry, but the distribution is a bell shape (high in the middle, low on two ends) (Figure 1). Thus, the data can be accepted as a normal distribution.

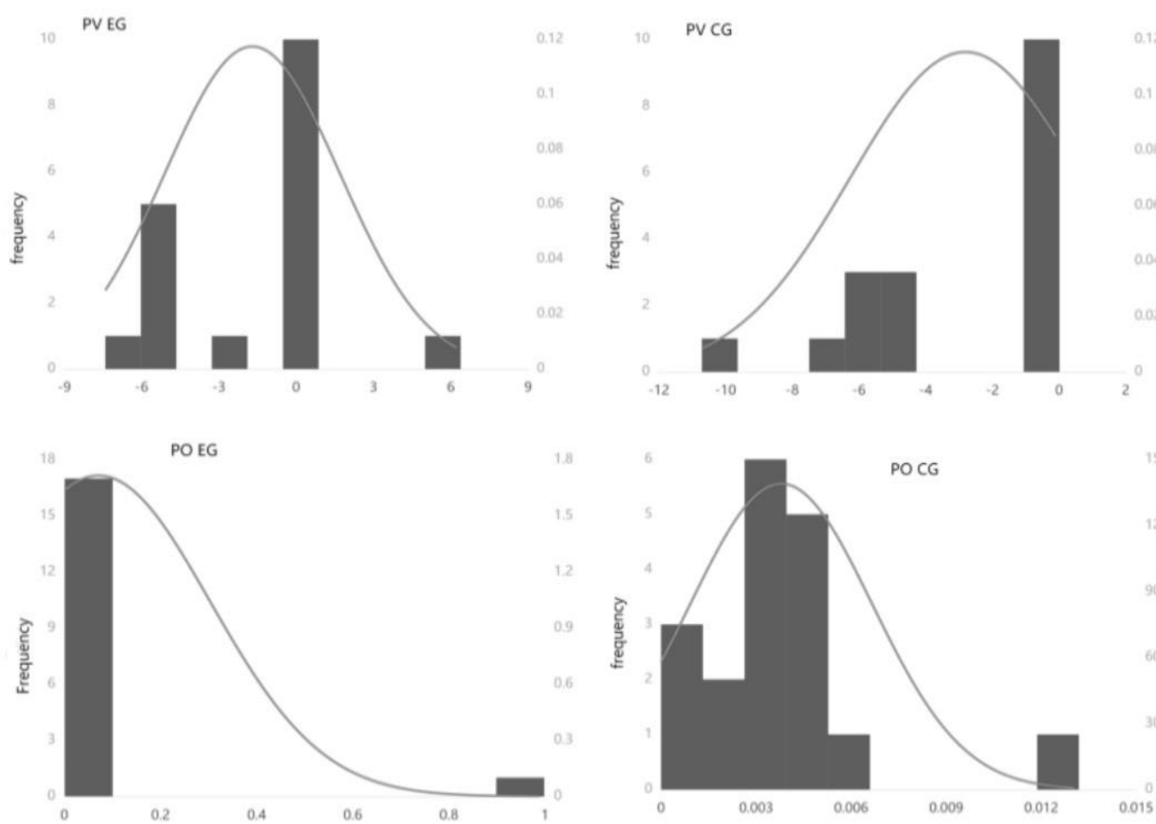

Figure 1 Normal distribution histogram

Table 8 Test for normality

Variable	n	median	mean	standard deviation	skewness	kurtosis	S-W test
M-score EG	22	-2.088	-1.606	2.05	0.882	0.004	0.912(0.052*)
M-score CG	22	-2.936	-3.11	20482	-0.626	2.589	0.929(0.118)

Variable	n	median	mean	standard deviation	skewness	kurtosis	S-W test
F-score PV EG	18	0.006	-1.7	3.397	0.245	0.379	0.839
F-score PV CG	18	0.001	-2.806	3.455	-0.756	−0. 546	0. 763

Variable	n	median	mean	standard deviation	skewness	kurtosis	S-W test
F-score PO EG	18	0.007	0.071	0.234	4.181	17.62	0.316
F-score PO CG	18	0.004	0.004	0.003	2.047	6.562	0.81

Note. * Refers to 10% significance

Second, a homogeneity variance test is also carried out. For M-Score, the significant level of value is 0.956 which suggests no rejection of the null hypothesis, so data for M-Score is valid for homogeneity variance. As for F-Score PE, the significant level of value is 0.551, also tested for homogeneity variance. But the significance value for PO is 0.0045 which rejects the null hypothesis. So, F-Score PV is not carried on for T-test (Table 9).

Table 9 Test for homogeneity variance

	Fscore PO（Stdev）		F	P
	EG(n=18)	CG(n=18)		
PO	0.232	0.003	4.32	0.045**
	Fscore PV（Stdev）		F	P
	EG(n=18)	CG(n=18)		
Predictiv e vlue	3.397	3.455	0.363	0.551
	Mscore（Stdev）		F	P
	EG(n=22)	CG(n=22)		
Mscore value	2.05	2.482	0.003	0.956

Note. **refers to 5% significance

An independent-samples t-test was used to check the difference in financial reports between companies committing financial fraud and those do not, for M-Score, t (21) =2.191, p= 0.034, with companies committing fraud associated with higher M-Score than the control group. (Fraud M= -1.606 Control mean= -3.1101); for predictive value, t (17) =0.967, p=1.106, but no significant difference was found (Fraud m=-1.701, Control m= -2.806) (Table 10).

Table 10 Result of T-test

Variable	value	n	mean	standard deviation	t value	p value
	EG	22	-1.606	2.05		
M-score	CG	22	-3.11	2.482	2.191	0.0034
	total	44	-2.358	2.375		

Variable	value	n	mean	standard deviation	t value	p value
	EG	18	-1.7	3.397		
F-score PV	CG	18	-2.806	3.455	0.968	1.106
	total	36	-2.253	3.423		

For M-Score, the difference between experimental groups is significant. But for F-Score, the significance is to be found.

5. Prevention of fraud

The fraud triangle explained that pressure, opportunity and rationalization are three drivers of corporate fraud. This is also what SAS No.99 underlines. To prevent fraud, we provide views on preventing fraud in terms of the above 3 perspectives.

5.1 Enhance internal control by improving corporate governance

Shareholders' overstated demands can bring overwhelming stress on the managers, while a strict appraisal system can put too much pressure on employees. Both of these conditions may result in accounting fraud if the internal control is ineffective since managers and employees may attempt to find opportunities to reach the expected goals. Defective internal control is usually correlated with inefficient corporate governance [8]. Therefore, firms must improve corporate governance.

5.2 Improve the accounting regulation and punishment mechanisms

The law is mandatory and enforceable, which means that the behaviors failing to comply with the regulations are amount to illegal. Ineffective regulation and punishment mechanisms can provide firms with opportunities and rationalization to escape from fraudulent behaviors. By contrast, comprehensive regulation and an effective punishment system can help prevent financial fraud, thus maintaining the capital market order. For firms, the public exposure to severe punishment can evoke the public's outrage at fraudulent behavior, thus raising firms' focus on the quality of financial reporting and disclosure compliance. Negative publicity can contribute to normative attitudes against corporate fraud and leads to the increasing willingness to invest in 'beyond-compliance' behaviors [9]. A comprehensive accounting regulation can alleviate information asymmetries in capital markets for investors. This will reduce investors' misunderstandings about corporate reporting and disclosure.

5.3 Improve audit quality through advanced technological approaches

The inability of auditing is another driver that creates "opportunity". The recent spate of accounting frauds of Chinese listed companies in the U.S. has not only exposed the companies' failure of corporate governance but also auditors' inability to detect financial fraud. Recently, the researcher found that machine learning algorithms would be helpful for audit authorities to discover accounting frauds [10]. In addition to common calculating models such as Beneish model and F-Score model, some advanced methods leveraging technology can be introduced into future auditing practice.

6. Conclusion

Financial fraud has always been a worry for investors in the capital market. Researchers have tried to find hints that help investors know the company's real performance. However, methods are still discovering. This research focuses on finding any clue of financial fraud of Chinese listed companies in the U.S. market using calculating models from the views of financial reports.

Using descriptive statistical analysis, this study estimates the use of a calculating model for Chinese companies listed in the United States that have a history of financial fraud. We select 7 sets of companies, i.e., 7 fraud companies and 7 companies without falsification. We use MScore and F-Score as the detector tools for financial fraud, and analyze the financial reports of the 7 sets of companies for 2-4 years including years before and after the fraud. In M-Score, most falsified companies have M-Score higher than -2.2 and a difference in data between experimental group and the control group has been detected. So, M-Score is useful in detecting financial fraud. On the other hand, most of the result of F-Score is lower than the value considered significant. Thus, F-Score is not recognized as useful in detecting fraud on financial reports.

There are, however, several important caveats to our methodology. First, our sample size is only 7 sets in total. This may result in poor representativeness of the statistical results. Second, we only select a small span of financial reporting years due to the impact of the timing of the listing and delisting of different companies. This may lead to unrepresentative accounting numbers and thus affect the analysis of MScore and F-Score. Third, in the data we collected, we discover in a few years the F-Score or M-Score of the control company is even higher than that of the fraud company (BILIBILI and WEIBO in 2020), which makes us re-evaluate our choice of control group. Since half of the sample companies come from the Internet industry and K-12 industry and many enterprises in these industries have been exposed to financial fraud, we cannot guarantee that the control group companies are free from the possibility of accounting fraud. And with further investigation, there is a major event, the COVID 19, happening in that particular year (2020), which may be a contributor to this result. Fourth, the Beneish model and Dechow's model were originally established to detect financial fraud in U.S. domestic listed companies. Applying these two models to U.S.-listed Chinese companies may not essentially fit very well with the conclusions of the models. Further, Dechow (2011) claims that F-Score can detect only misstatements which were identified by the SEC [4]. Whereas the accounting frauds of the sample companies in our research were mostly caught by third-party institutions.

Besides, F-Score and M-Score mainly evaluate the changes in some items in financial report. The first problem is that not all items in the financial report are covered, such as investing cash flow. Companies that manipulate their figure in these items will not be detected. The second concern is that more M and F Score models calculate change within two years, so if a company constantly frauds in same item of their financial report, their fraud is likely not to be detected.

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