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Research on Financial Fraud Identification of Agricultural and Mining Listed Companies
-- Based on Factor Analysis

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ABSTRACT
This paper analyzes the accounting fraud of listed agricultural and mining companies by constructing the fraud risk index, selecting 23 indicators according to the fraud theory and means, takes the agricultural and mining listed companies punished by the CSRC in recent five years as the sample, and constructs the accounting fraud identification model of listed companies by using the factor analysis method and the accounting fraud risk index. It is found that the construction of a comprehensive accounting fraud risk index to describe the accounting fraud risk of listed companies has high accuracy, and it is also conducive to the identification and early warning of potential accounting fraud of listed companies.

Keywords: *Fraud theory; Accounting fraud; Factor analysis model; Fraud risk index*

1. INTROODUTION

Accounting fraud refers to the deliberate fraud of the management of listed companies to maximize their interests by taking means to implement significant misleading financial reports, which is detrimental to the interests of shareholders and creditors[1]. Accounting fraud of listed companies has always been one of the "persistent diseases" of the securities market. Based on the administrative punishment letter issued by the CSRC, there have been more than 100 listed companies involved in accounting fraud in China's securities market in the five years from 2015 to 2020, including agricultural and mining listed companies, which are highly prone to accounting fraud, Among the listed companies punished by the CSRC, financial fraud accounted for more than 30%. Based on this, this paper takes the agricultural and mining listed companies as the research sample, constructs a model for the characteristics of agricultural and mining listed companies, and can effectively identify fraud based on the existing research results, to provide early warning for the audit risk identification and risk control of agricultural and mining listed companies.

2. JOURNALS REVIEWED

At present, the research on the identification of accounting fraud at home and abroad has been quite in-depth, including not only the research on the theory of accounting fraud but also the empirical research on the indicators and models of accounting fraud identification. (1) In terms of fraud theory, Albrecht first proposed the triangular theory of fraud motivation, which believes that the motivation of corporate fraud comes from pressure, opportunity, and excuse[2], that is, there is pressure to commit fraud, opportunity to commit fraud and being able to find an excuse to rationalize their behavior[3]. Specific to China's capital market, the causes of fraud mainly include fraudulent listing, financial difficulties, delisting pressure, allotment of shares, tax evasion, fictitious profits to maximize personal remuneration[4]. (2) In terms of the construction of a fraud identification index system, the index selection mainly includes questionnaire survey, financial report analysis, big data technology mining model[5], and various characteristic variables. (3) In the construction of the fraud identification model, statistical analysis is the most used. Some scholars select the control sample companies to build the logistic regression model[6] or use *Benford* law to establish a new logistic model containing *Benford* factors[7]. Other models include the financial report fraud discrimination model based on artificial neural system network technology[8][9], two-layer combined neural network fraud risk identification model based on *BP-LVQ*[10], and case-based reasoning model using training set samples and test set samples[11]. In addition, in the era of big data, artificial intelligence has also begun to be applied and studied. It mainly includes deep learning algorithm[12], intelligent financial report fraud identification model combined with MD & a text[13], financial fraud identification model based on data mining classification technology[14], etc. (4) In terms of fraud prevention and governance, the governance path includes governance through the concept of senior management, control activities[15], improving the supervision function of external audit, establishing a reasonable management incentive system[16], and elaborating the evolutionary game between fraudulent enterprises, accounting firms, and regulatory authorities[17].

To sum up, the research on accounting fraud identification mostly focuses on the fraud identification model, and the research objects are mostly listed companies that have committed fraud, and there is less research on the evaluation of potential fraud risk of non-fraud companies. And although foreign research is very mature. However, the scope of research is mainly American and British countries. The research background is mostly based on its perfect and mature external governance market. This limits the applicability of the research conclusions to solve the problem of fraud in China's capital market to a certain extent. The-accounting fraud risk index has the advantage of reflecting the refinement of fraud risk. Domestic scholars have discussed the fraud risk index system and the selection method of index threshold and constructed and tested the fraud risk index model[18] . Inspired by this, this paper takes the listed companies in the agricultural and mining industry with a high incidence of fraud as the sample, and studies the construction of accounting fraud risk index based on factor analysis. By depicting the cumulative score of the company's accounting fraud risk degree, this paper reflects its accounting fraud risk degree, to warn investors or creditors to choose the right investment object and maintain the order of the capital market.

3. RESEARCH DESIGN

3.1. Sample Selection and Data Source

This study selects listed companies in the agricultural and mining industry as the selection scope and is divided into fraud and non-fraud. Compared with existing studies, when determining the scope of fraud samples, four types of violations of "fictitious profits, fictitious assets, false disclosure, and false records (misleading statements)" are included in the selected range. At the same time, to avoid the impact of abnormal results of data on the research results of this paper, and ensure the support of data and the accuracy of analysis results, the sample companies are screened. □ Eliminate listed companies with shortlisting time; □ Exclude listed companies that have been delisted during the study period; □ Exclude listed companies with incomplete financial data. According to the screening results and the division of industries by the CSRC, the 2019 annual report data of 47 A-share agricultural, forestry, animal husbandry, fishery, and mining listed companies in Shanghai and Shenzhen were finally selected as the research samples. Some of the data used in the research came from the Guotai'an database, wind database, and economics network, and some were calculated according to the report data disclosed by the listed companies..

Table 1 Sample Company Code

Stock Code of A-Share Market						
600121	300157	002683	600256	601020	300087	300313
600311	600097	300498	600403	601101	300189	000923
600338	600257	600313	600759	601168	000426	002192
600395	601118	002124	600985	000655	000506	002207
600758	002086	002679	601069	000762	000603	002554
600777	002157	002772	601969	000735	000998	002069
600988	002458	300106	000592	002629		

3.2. Main Variable Indicators

Fraud triangle theorists believe that the main factor of corporate fraud is stress, which comes from the deteriorating financial situation. Therefore, the financial indicators of enterprises are selected and divided into vertical financial indicators and horizontal financial indicators.

Table 2 Accounting Fraud Risk Index

Category	Indicator Name	Category	Indicator Name
	Receivables turnover index		Receivable turnover days
	Change index of receivables		Turnover days of other receivables
	Turnover index of other receivables		Inventory turnover days

Vertical Financial Indicators	Change index of other receivables	Horizontal Financial Indicators	Asset quality
	Inventory turnover index		The proportion of non main business income
	Inventory change index		Period expense rate
	Depreciation index of fixed assets		Surplus cash flow difference
	Asset quality index		Operating accrued profit
	Operating revenue growth index		Cash sales ratio
	Period cost index		Cash flow liability ratio
	Gross margin index		The proportion of other operating cash flows
	Degree of accrued earnings management		

A Vertical indicator is an analytical indicator for cross-year vertical comparison of financial indicators of sample companies in two or more consecutive accounting periods, dividing the current period value by the previous period value. For example, the asset quality index (1 - (current assets + net fixed assets) / total assets) t / (1 - (current assets + net fixed assets) / total assets) t-1) measures other soft assets except fixed assets and current assets. The larger the index, the higher the fraud risk of the company's inflated assets. Others include fixed assets depreciation index, period cost index, gross profit rate index, and so on.

Horizontal indicators identify the risk of accounting fraud by analyzing the structure and ratio of relevant items in the balance sheet, income statement, and cash flow statement in the current financial report. They are divided into balance sheet indicators, income statement indicators, and cash flow statement indicators.

4. EMPIRICAL ANALYSIS

4.1. Factor Applicability Test

Here, KMO and Bartlett tests are used to determine whether there is course elation between the selected variables and whether it is suitable for factor analysis. The test results are as follows: the significance probability of KMO value and Bartlett sphere test in 2019 passed the test, in which the KMO value is between 0~1, and the significance probability of Bartlett sphere test value is less than 0.01, indicating that the selected index data is suitable for factor analysis.

Table 3 KMO and Bartlett Test

KMO Sampling Suitability Quantity		.646
Bartlett Sphericity Test	Approximate Chi-Square	912.213
	df	253
	Sig.	.000

4.2. Calculate Eigenvalue and Variance Contribution Rate

Generally speaking, the more common factors are extracted, the greater the variable information that the factor model can explain. Therefore, the model is also more accurate. However, if too many factors are extracted, it is difficult to simplify the variables. Factor analysis is meaningless. Therefore, the interpretation rate of the extracted factors to the original variables is generally more than 80.00%. The eigenvalue is generally greater than 1. We take the factor greater than 1 as the common factor and the factor less than 1 as the common factor.

Table 4 Gravel Diagram of Each Component

Factor	Initial Eigenvalue			Extract Sum of Squares Load			Rotational Sum of Squares Load		
	Total	Variance Contribution Rate	Cumulative Contribution Rate	Total	Variance Contribution Rate	Cumulative Contribution Rate	Total	Variance Contribution Rate	Cumulative Contribution Rate
1	5.122	22.268	22.268	5.122	22.268	22.268	4.984	21.669	21.669
2	3.699	16.081	38.349	3.699	16.081	38.349	3.095	13.455	35.124

3	3.156	13.723	52.072	3.156	13.723	52.072	2.706	11.767	46.891
4	2.692	11.706	63.778	2.692	11.706	63.778	2.301	10.005	56.896
5	1.844	8.018	71.796	1.844	8.018	71.796	2.277	9.900	66.796
6	1.195	5.197	76.993	1.195	5.197	76.993	1.890	8.219	75.015
7	1.028	4.470	81.462	1.028	4.470	81.462	1.418	6.164	81.179
8	1.044	4.540	86.002	1.044	4.540	86.002	1.109	4.823	86.002
Extraction method: Principal Component Analysis.									

According to SPSS25.0 software can obtain the variance contribution rate of each factor of 2019 sample data. The principal components are arranged according to the variance contribution rate. There are 8 factors with eigenvalues greater than 1 in total. In descending order. The table contains information about "extracted sum of squares load" and "rotating sum of squares load". It can be seen that the eight common factors include 86.002% of the information of 23 original variables. This shows that the eight common factors extracted can reflect most of the information. It can be used as the data support for the research of accounting fraud identification of sample listed companies.

4.3. Establish Factor Load Matrix

Table 5 Factor Load Matrix After Rotation

Index Component	1	2	3	4	5	6	7	8
Zscore X_1	0.307	0.489	-0.059	0.061	0.106	0.378	-0.211	0.008
Zscore X_2	0.055	-0.001	0.878	-0.002	0.001	0.079	-0.058	-0.039
Zscore X_3	0.011	-0.045	-0.029	0.878	-0.098	0.048	0.003	0.005
Zscore X_4	0.041	0.016	-0.047	-0.193	0.832	0.032	-0.080	0.018
Zscore X_5	0.313	-0.02	0.081	0.015	0.525	-0.189	-0.013	0.612
Zscore X_6	0.063	0.014	-0.033	0.811	-0.026	0.134	-0.063	-0.020
Zscore X_7	0.024	0.967	-0.015	-0.080	-0.017	0.022	0.011	0.108
Zscore X_8	-0.034	0.938	-0.027	-0.001	0.138	-0.092	-0.031	-0.256
Zscore X_9	0.889	-0.152	-0.041	0.031	-0.056	0.895	0.105	-0.061
Zscore X_{10}	0.087	0.051	0.086	0.072	0.016	0.816	0.052	0.007
Zscore X_{11}	0.403	0.014	0.084	0.080	0.250	0.199	0.104	0.773
Zscore X_{12}	0.858	0.861	-0.065	0.011	-0.227	0.203	0.023	-0.072
Zscore X_{13}	0.988	-0.009	0.016	0.006	0.035	-0.133	-0.151	-0.083
Zscore X_{14}	-0.130	-0.307	0.618	0.681	-0.816	-0.065	-0.313	0.036
Zscore X_{15}	0.344	0.102	0.735	-0.079	-0.211	0.131	-0.195	0.062
Zscore X_{16}	0.033	-0.051	0.968	-0.025	-0.093	0.022	-0.059	-0.015
Zscore X_{17}	0.972	-0.021	-0.027	-0.006	0.022	-0.099	-0.081	-0.069
Zscore X_{18}	-0.039	0.019	0.033	0.010	0.325	-0.232	0.088	0.112
Zscore X_{19}	0.089	-0.218	0.078	-0.051	-0.518	-0.013	-0.241	0.010
Zscore X_{20}	-0.020	0.065	-0.007	-0.007	0.098	0.106	0.746	-0.07
Zscore X_{21}	-0.307	-0.253	-0.153	0.580	-0.202	-0.103	0.361	0.008
Zscore X_{22}	0.945	0.079	0.029	0.046	0.070	-0.04	-0.057	-0.089
Zscore X_{23}	-0.174	-0.201	-0.092	0.015	0.029	-0.03	0.639	0.078

According to table 5, it can be analyzed that:

The main factor F_1 has a significant correlation with the variables accounts receivable turnover index, inventory turnover index, period cost index, and operating income growth index. These variables are related to income (operating income, non-operating income, investment income, etc.), so they are called the income fraud factor.

The main factor F_2 has a large load on the difference of surplus cash flow and operating accrued profit. These variables are related to the difference between surplus and cash flow, so it is called accrued profit fraud factor.

The main factor F_3 has a large load on other accounts receivable turnover days, other accounts receivable change indexes, and other accounts receivable turnover indexes. These variables are related to other accounts receivable, so it is called the other accounts receivable fraud factor.

The main factor F_4 has a large load on inventory turnover days, period expense rate, and accounts receivable turnover index. These variables are related to operating revenue, operating cost, inventory, etc. They are all related to sales business, so they are called sales business fraud factors.

The main factor F_5 has a large load on the turnover index of accounts receivable and asset quality. These variables are related to the risk of fraud through expense capitalization, so it is called the expense capitalization fraud factor.

The main factor F_6 has a large load on the sales cash ratio, the change index of accounts receivable, and the cash flow liability ratio. These variables are related to the debt repayment pressure index, so it is called the cash debt repayment pressure fraud factor.

The main factor F_7 has a large load on the asset quality index and gross profit rate index. These variables are related to the change speed of the number of soft assets to the asset quality, so it is called the soft asset management fraud factor.

The main factor F_8 has a large load on the proportion of other operating cash flow and non-main business income. These variables are related to the proportion of cash inflow from other businesses other than main business income, non-operating income, and other receivables, so it is called the non-main income (income from low-quality operating activities) fraud factor.

Table 6 Component Score Coefficient Matrix

Index / Component	1	2	3	4	5	6	7	8
Zscore X_1	0.030	0.139	-0.080	-0.015	0.132	0.279	-0.151	0.032
Zscore X_2	-0.031	0.014	0.459	0.009	0.012	-0.008	0.060	-0.052
Zscore X_3	-0.002	0.020	0.005	0.484	-0.037	-0.065	0.066	0.011
Zscore X_4	0.010	-0.120	-0.04	-0.107	0.449	0.076	-0.146	0.093
Zscore X_5	0.006	-0.045	0.049	0.004	0.194	-0.097	-0.004	0.518
Zscore X_6	-0.002	0.027	-0.01	0.464	-0.006	-0.016	0.014	-0.019
Zscore X_7	-0.021	0.441	0.013	0.007	-0.115	-0.047	0.058	0.122
Zscore X_8	-0.094	0.402	0.014	0.029	0.008	-0.096	-0.006	-0.199
Zscore X_9	-0.047	-0.114	-0.052	-0.045	0.030	0.460	-0.010	-0.196
Zscore X_{10}	0.009	-0.031	0.043	-0.026	0.078	0.397	0.011	0.032
Zscore X_{11}	0.124	0.027	0.084	0.045	0.140	0.061	0.174	0.498
Zscore X_{12}	0.204	-0.073	-0.071	-0.025	-0.087	0.092	0.076	0.004
Zscore X_{13}	0.228	-0.067	-0.031	-0.007	0.018	-0.07	-0.017	0.024
Zscore X_{14}	-0.045	-0.209	0.096	0.117	-0.372	-0.007	-0.276	0.051
Zscore X_{15}	0.125	0.105	0.119	-0.057	-0.117	0.039	-0.028	0.186
Zscore X_{16}	-0.029	0.005	0.464	-0.01	-0.011	-0.033	0.067	-0.031
Zscore X_{17}	0.247	-0.074	-0.053	-0.018	0.008	-0.053	0.025	0.032
Zscore X_{18}	0.062	-0.033	0.040	0.046	0.225	-0.107	0.050	0.193

Zscore X_{19}	0.039	-0.026	0.007	-0.05	-0.121	-0.005	-0.100	0.047
Zscore X_{20}	0.051	0.048	0.083	0.036	0.003	0.001	0.552	-0.067
Zscore X_{21}	-0.027	-0.130	-0.033	-0.074	-0.050	-0.028	0.195	-0.03
Zscore X_{22}	0.230	-0.017	-0.015	0.022	0.014	-0.041	0.049	0.022
Zscore X_{23}	0.032	-0.068	0.024	0.048	0.002	-0.033	0.388	0.099

4.4. Factor Score

According to the rotated factor score coefficient matrix and the index value of the original variable, the score of each common factor can be determined. The expression of factor analysis is:

$F_1=0.030*X_1-0.031*X_2-0.002X_3+...+0.032*X_{23}$

$F_2=0.139*X_1+0.014*X_2+0.020X_3-...-0.068*X_{23}$

$F_3=-0.080*X_1+0.459*X_2+0.005X_3-...+0.024*X_{23}$

$F_4=-0.015*X_1+0.009*X_2+0.484X_3-...+0.048*X_{23}$

$F_5=0.132*X_1+0.012*X_2-0.037*X_3+0... +0.002*X_{23}$

$F_6=0.279*X_1-0.008*X_2-0.065*X_3+... -0.033*X_{23}$

$F_7=-0.151*X_1+0.60*X_2+0.066*X_3-... +0.388*X_{23}$

$F_8=0.032*X_1-0.052*X_2+0.011*X_3+... +0.099*X_{23}$

4.5. Construction of Accounting Fraud risk Index

Taking the variance contribution rate of each factor after rotation as the weight, the weighted sum of the eight factors is defined as the total fraud risk index.

$F_{index}=0.21669*F_1+0.13455*F_2+0.11767*F_3+0.10005*F_4+0.09900*F_5+0.08219*F_6+0.06164*F_7+0.04823*F_8$

Table 7 Factor Score and Rank

Code	F_{index}	Rank	Code	F_{index}	Rank	Code	F_{index}	Rank	Code	F_{index}	Rank
000426	0.247	9	600759	-0.164	31	600395	-0.174	33	300189	0.524	3
000506	0.364	8	600985	-0.162	30	600758	0.123	16	300313	0.075	18
000603	-0.423	45	601069	-0.435	46	600777	0.123	15	300498	-0.409	44
000923	0.193	10	601969	-0.209	35	600988	-0.269	38	600313	-0.387	42
002192	0.508	4	000592	0.108	17	601020	-0.112	26	002124	-0.164	32
002207	-0.215	36	000735	-0.084	24	601101	-0.060	23	002679	0.455	5
002554	0.133	14	000998	-0.023	21	601168	-0.365	41	002772	-0.327	40
002629	1.571	1	002069	-0.118	27	000655	-0.183	34	300106	-0.108	25
002683	-0.141	29	002086	0.715	2	000762	0.387	7	600097	-0.269	37
600121	-0.052	22	002157	0.161	11	300157	0.406	6	600257	-0.138	28
600311	0.140	12	002458	-0.635	47	600256	-0.020	20	601118	-0.401	43
600338	0.137	13	300087	-0.307	39	600403	0.072	19			

4.6. Evaluation Results

4.6.1 Score Analysis of Each Fraud Factor

The five companies with the highest scores in terms of income fraud factors are "Zhejiang Renzhi", "Xingye Mining" and" Quasi Oil Shares". The score of "Zhejiang Renzhi" is 6.42. This is much higher than the 0.73 scores of "Xingye Mining", which ranks second. This shows that "Zhejiang Renzhi" has the highest risk of income fraud. At this time, items such as operating income, the accrued profit, and other business income have become the focus of the audit. In the punishment disclosed by the Shenzhen Stock Exchange in 2020, "Zhejiang Renzhi" was filed for punishment by the CSRC because of fictitious business income and profits, illegal disclosure, and false records (misleading statements). This also verifies the rationality of the factor score constructed in this paper. The two companies with the lowest scores are "Hegang Resources" and "Chifeng Gold". Their scores were -0.656 and -0.625 respectively. This shows that the two companies have a low risk of fraud in revenue items.

The top three companies in terms of accrued profit fraud factors are "Liaoning energy", "Rongjie Shares" and "Oriental Ocean". Their scores were 3.90, 2.67, and 1.75 respectively. The score is much higher than the sample mean. It shows that these three companies have the highest risk of fraud in accrued profits. At this time, whether the operating accruals match the cash flow and why they deviate seriously are the important risk points that the audit pays attention to. The two companies with the lowest scores are "Western Gold" and "Prebiotic Shares". Their scores were -1.46 and -1.27 respectively. This shows that the two companies have a low risk of fraud in profit items. The other factor analyses were similar.

4.6.2 Score Analysis of Fraud Index

The fraud risk index can comprehensively evaluate the scope or degree of the company's fraud risk, and the ranking can roughly measure the fraud risk. If the index ranking is not high, but some indexes rank high, it indicates that there is a high risk of fraud on this sub-index. Individual fraud factors facilitate the accurate identification of fraud risk points. In 2019, the top five listed companies in the comprehensive score of the accounting fraud index of 47 sample listed companies were "Zhejiang Renzhi, Oriental Ocean, Shennong Technology, Rongjie Shares, and Fujian Jinshan". The three lowest listed companies are "Yisheng Shares, Western Gold, Shengda Resources".

The listed company with the highest score of fraud risk index and the highest degree of fraud risk is "Zhejiang Renzhi". It has high scores in the first, second, third, fourth, fifth, seventh, and eighth factors. More specifically, the scores of income fraud factor F1 and income fraud factor F8 of non-main activities are the highest. It can be seen that the company's indicators X5, X11, X13, X17, X21, and X22 rank first among the sample companies The scores of other fraud factors, such as accrued profit fraud factor, other receivables fraud factor, sales business fraud factor, expense capitalization fraud factor, and asset management fraud factor, are also high. This is consistent with the fact that "Zhejiang Renzhi" has had a negative net profit for two consecutive years and is facing a delisting crisis. Only by manipulating income, adopting expense capitalization to reduce current expenses, or not withdrawing depreciation reserves to reduce current asset impairment losses, can we turn losses into profits and make the net profit positive. Then take off the hat of ST and get rid of the risk of delisting pressure, which is consistent with the logic.

The listed company with the lowest score of fraud risk index is "Prebiotic Shares". It has a low risk of fraud in 2019. But its seventh-factor score is slightly higher. Therefore, the fraud risk points of the company's key audit are inventory, fixed assets, accounts receivable, income, and expense capitalization.

5. CONCLUSION

This paper analyzes the definition of accounting fraud and its related fields basis on an accounting fraud theory. Selecting financial and non-financial indicators as variables, this paper constructs the accounting fraud identification index system and constructs the fraud risk index identification model based on the dimensionality reduction analysis of variables by using the factor analysis method. From the research on the results of accounting fraud risk index, the pressure of accounting fraud of listed companies mostly comes from the management due to external financing, industry competition The combination of performance commitment, and personal financial needs, to seek and create corresponding fraud opportunities. The risk points of accounting fraud mainly focus on the items of balance sheet fraud and income statement fraud. In addition, investment income and government subsidies have also become new objects for managers to manipulate profits. The comprehensive analysis of the accounting fraud risk index can help to grasp the fraud risk of listed companies prospectively and reduce the investment risk of investors. It can also provide detailed and specific reference indicators for the anti-fraud work of regulatory authorities and escort the healthy development of the capital market.

AUTHORS' CONTRIBUTIONS

Zeshuang Liu: Professor and Doctor of the Xi'an University of Technology, Executive Director of China Human Resources Development Teaching and Practice Research Association, Member of China Aerospace Qian Xuesen Innovation Committee, Director of Human Resources Management Institute of the Xi'an University of Technology.

Xue Deng: Postgraduate of the Xi'an University of Technology.

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REFERENCES

[1]Chandra S. Throckmorton,William J.Mayew,Mohan Venkatachalam,Leslie M. Collins. Financial fraud detection using vocal,linguistic and financial cues[J].Decision Support Systems,2015,74.

[2]Albrecht W S , Wernz G W ,Williams T L. Fraud : bringing light to the dark side of business [M].Irwin Professional Pub.1995.

[3]Albrecht W S ,Romney M B .Red-flagging management fraud:Avalidation.1986.

[4]Guanjun Tian,Nan Yao.Identification and control of financial fraud audit risk of agricultural listed companies—Multi case analysis based on gone theory[J].Accounting communication,2016(19): 93-95.

[5]Petr Hajek,Roberto Henriques.Mining corporate annual reports for intelligent detection of financial statement fraud—A comparative study of machine learning methods[J].Knowledge-Based Systems,2017,128:

[6]Zenglian Zhang, Ya Gao. Construction of financial fraud identification model and empirical test [J]Statistics and decision making,2017(09):172-175.

[7]Guijun Yang, Yameng Zhou, et al.Logistic model based on Benford law and its application in financial fraud identification[J]Statistics and Information Forum,2019,34(08):50-56.

[8]Green B P, Choi J H. Assessing the Risk of Management Fraud Network Technology[J].Auditing:A Journal of Practice&Theory,1997.I6(1):14-28.

[9]Spathis C T.Detectung false financial statement using published data:some evidence from Greece [J].Managerial Auditing Journal,2002,17(4):179-191.

[10]Zexia Wang, Ding Gao et al.Research on combined neural network fraud risk identification model based on bp-lvq—Empirical Evidence from Chinese fraudulent listed companies[J]Productivity research,2017(12):145-151.

[11]Qing Li,Zhenglei Dang.Research on the construction and evaluation of accounting fraud risk index--Based on factor analysis[J] Mathematical statistics and management,2019,38 (06):1048-1061.

[12]Chandra S. Throckmorton,William J. Mayew,Mohan Venkatachalam,Leslie M. Collins. Financial fraud detection using vocal, linguistic and financial cues[J].Decision Support Systems,2015,74:

[13]Nahui Zhao, Tianyang Zhang.Financial report fraud identification based on MD & a text and deep learning model[J/OL]Friends of accounting:1-10[2022-01-06].

[14]Kirkosa E,Spathisb C,Manolpoulsc Y.Data mining techniques for the detection of fraudulent financial statements[J].Expert Systems with Applications,2007,32(4):995-1003.

[15]Treadway Committee.Fraud Commission Issues Final Report[J].Journal of Accountancy,1987(11).

[16]Yan Zhang, Yaying Lao.Behavior means and governance mechanism of financial fraud of Listed Companies[J]Enterprise reform and management,2021(15):131-132.

[17]Jihui Sun, Ziqi Shen.Research on the impact of social audit supervision on audit collusion based on evolutionary game model[J]Accounting communication,2021(23):123-127.

[18]Qing Li, Zehan Ma.Construction and early warning of accounting fraud risk index--Taking Listed Companies in Jilin Province as an example [J]China Management Informatization,20 19,22 (11):31-33.