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Identification on Financial Fraud by Companies Using the Logistic Regression Model

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Abstrak
Kecurangan keuangan oleh perusahaan memiliki efek negatif terhadap kepercayaan dan loyalitas semua pemangku kepentingan serta efisiensi pasar dalam mengalokasikan aset. Penelitian ini bertujuan untuk mengidentifikasi kecurangan keuangan secara cepat dikembangkan, dengan menggunakan Model Regresi Logistik untuk membangun sistem indeks. Perusahaan-perusahaan Cina yang terdaftar dalam database China Stock Market & Accounting Research menjadi fokus investigasi; industri berikut tidak termasuk: J67 (jasa pasar modal), J68 (industri asuransi), J69 (industri keuangan lainnya), J66 (industri keuangan lainnya kecuali jasa moneter dan keuangan). Penyelidikan akan berlangsung antara tahun 2017 dan 2020. Sebanyak 53 bisnis palsu dan 53 bisnis Cina yang sah termasuk dalam sampel data. Berdasarkan hasil penelitian diperoleh nilai akurasi prediksi total model adalah 83%. Untuk meningkatkan efektivitas identifikasi penipuan keuangan dari stan teknologi

Kata Kunci: penipuan mata uang kripto, laporan keuangan, aktivitas investasi, model regresi logistik

Abstract
Financial fraud by companies has a negative effect on the trust and loyalty of all stakeholders as well as market efficiency in allocating assets. This study aims to identify financial fraud in a rapidly developed manner, using the Logistic Regression Model to build an index system. Chinese companies listed in the China Stock Market & Accounting Research database were the focus of the investigation; the following industries were excluded: J67 (capital market services), J68 (insurance industry), J69 (other financial industries), J66 (other financial industries except monetary and financial services). The investigation will take place between 2017 and 2020. A total of 53 fake businesses and 53 legitimate Chinese businesses are included in the data sample. Based on the research results, the total prediction accuracy value of the model is 83%. To improve the effectiveness of financial fraud identification from technology booths

Keywords: cryptocurrency fraud, financial statement, investment activities, logistic regression model

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INTRODUCTION

A number of incidents involving corporate financial fraud have surfaced in the securities markets of different nations in recent years. Financial fraud is divided into four categories by Al-Hashedi and Magalingam (2021): bank fraud, insurance fraud, financial statement fraud, and cryptocurrency fraud. Additionally, research by Kuzior and Kwilinski (2022), Bharadwaj and Deka (2021), Gajdzik et al. (2021), and Miśkiewicz (2019) highlights the positive impact of digital technology development on a company's financial success. Additionally, it creates more opportunities for deception. According to researchers Aggarwal et al. (2015), Wu et al. (2016), Liang et al. (2022), and Al-Hashedi and Magalingam (2021), financial fraud is a major problem for the financial industry and affects the loyalty and trust of all parties involved in a company (banks, investors, creditors, government, consumers, society). According to Choi & Lee (2018), Al-Hashedi & Magalingam (2021), and West & Bhattacharya (2016), financial fraud is defined as financial abuse, which is defined as unlawful or illegal behavior that benefits people or organizations in unethical and illegal ways. Financial fraud causes financial and reputational losses for investors, the government, the corporate sector, and the company's shareholders. According to Ewelt-Knauer et al. (2015), the disclosure of information about financial wrongdoing causes a fall in shareholder values in German corporations. Between 1998 and 2014, the total amount of losses was, on average, 81 million euros. According to Qiu et al. (2021) and Carleton (2021), the financial fraud incident involving Luckin Coffee in 2020 led to the expulsion of certain businesses from the Chinese stock exchange, resulting in a negative impact on the reputation of other listed companies. These incidents support the government's appropriate response, which primarily aims to give Chinese corporations more financial leverage.

The People's Republic of China (2020) Securities Law was released in 2020 and toughened the penalties for financial fraud committed by businesses. Although Wang and Wang (2022) and Lu (2021) point out, the new law enhances the punishment for financial fraud committed by an enterprise, but it hasn't had the expected impact. Primarily, this is because the benefits of fraud for businesses result in large profits, which enable them to pay off the costs and penalties associated with fraud. To eradicate financial fraud among the listed firms, the Shenzhen Stock Exchange created the Guide on Information Disclosure Evaluation Systems for Firms Listed in the SZSE in 2001 (Ho et al., 2022). All of this should be acknowledged. The most recent revision of this document was released in 2020 after five revisions. Taking this approach into account, there should be two steps involved in fraud identification: The first step is to describe the characteristics and prerequisites of financial fraud (index system design); the second is to create an identification model that might influence how well fraud is identified. The severe negative effects of financial fraud drive specialists and academics to create methods for spotting financial fraud. But the majority of studies (Ren et al., 2021; Su et al., 2021; Liang et al., 2022; Zhao et al., 2021; Xu et al., 2022) cantered more on financial fraud than on corporate fraud.

This study solves a research gap by 1) defining the key determinants, impulses, and elements of financial fraud and adding to the theoretical foundation; and 2) establishing a timely identification approach of financial fraud based on index system development. The goal of this study is to create a model that uses index system development to identify financial fraud in the organizations. There will be four sections to the paper. The first section reviews the literature and analyses the theoretical underpinnings of financial fraud as well as the methods used to spot it early. In order to accomplish the goals of the article, the second part lists sources for data compilation and provides an explanation of the tools and methods used. The examination of the investigation's empirical findings is presented in the results and discussion section. The conclusion is the concluding part, where the main findings are summarized, the limits are highlighted, and future research prospects are outlined.

METHODOLOGY

The balance sheet, income statement, and cash flow statement are the primary financial statements that show the outcomes of a company's operations (Fedorko et al., 2021; Zadorozhnyi et al., 2021; Kwilinski et al., 2020). Fig. 1 shows the several relationships between the internal elements and the company's cash flow, operating performance, and financial status.

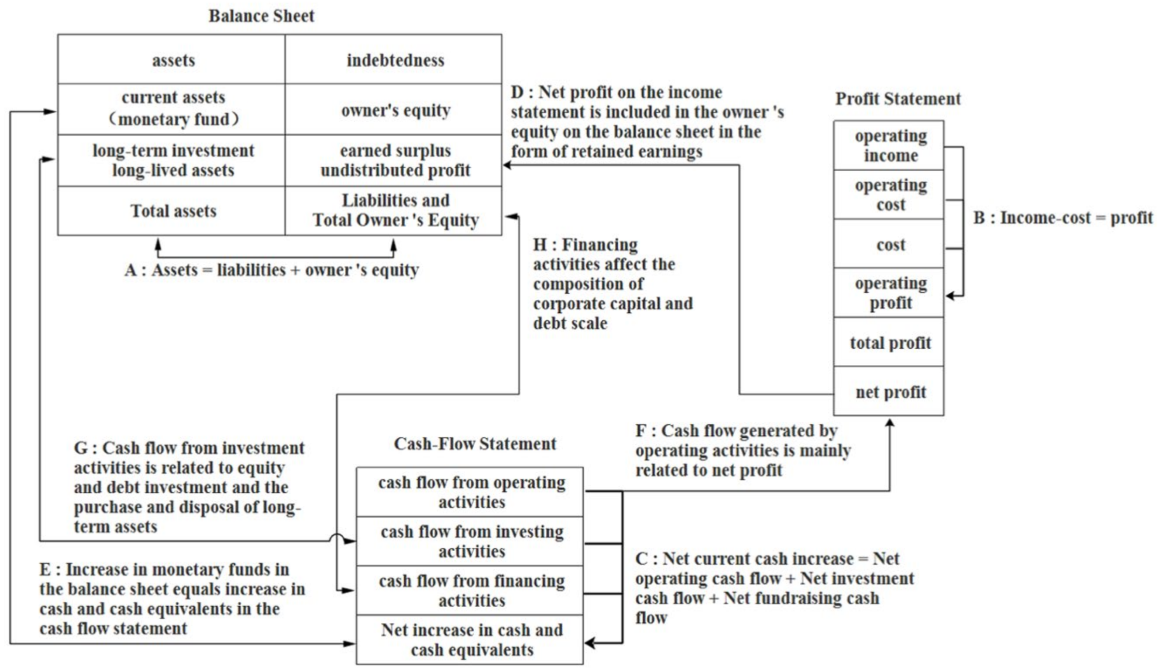

Fig. 1 – The diagram of the relationship between three major enterprise financial statements

The analysis's internal components exhibit many associations, as shown by the parameters A, B, and C (Figure 1). D demonstrates how, despite altering the asset project, the production and operational outcomes of each enterprise period ultimately return to the owner's equity in the form of retained revenue. According to Relationship E, changes in monetary funds are equal to the net rise in cash and cash equivalents following the three key activities. Relationship F demonstrates that a firm's business operations are primarily responsible for generating profits, and the cash flow these activities produce may be used to assess the net profit quality of the enterprise. Relationship G demonstrates that the acquisition and sale of long-term assets as well as equity loan investments account for the majority of the cash flow associated with investment activities. Relationship H suggests that the capital and debt structure of a business will be impacted by the cash flow from financing operations. The enterprise's dishonesty is shown by the anomalous relationship between the items in the balance sheet and the income statement from its primary operations (operation, investment, financing, and synthetics judgment)

RESULT AND DISCUSSION

The fraud sample for the study's 2017–2020 period is made up of businesses that have financial infractions listed in the China Stock Market and Accounting Research (2022) database (CSMAR). There are two guidelines for screening:

1). for businesses that have consistently broken the law over a long period of time. In order to avoid the potential for overestimation of fraud due to recurrent sample extraction, the first violation year is chosen as the fraud period to extract data samples. 2). The figures from the financial sector varies significantly from that of other sectors. According to the industry classification standard of the CSRC (China Security Regulatory Commission) version 2012, financial enterprises whose main categories are J66 (remaining financial industry except for the monetary and financial services), J67 (capital market services), J68 (insurance industry), and J69 (other financial industry) are excluded. This allows the CSRC to compile a sample of fraudulent enterprise which is in the same industry and has the closest total assets. Lastly, 53 legitimate and 53 fraudulent businesses are included in the data sample. SPSS26 is utilized in the empirical investigation for data analysis. Tab. 1 displays the findings of the descriptive statistics analysis.

Table 1 – The findings of descriptive statistics

Fraud		N	Mean	St. Dev	Fraud		N	Mean	St. Dev	Fraud		N	Mean	St. Dev
X1	1	53	1.95	5.60	X7	1	53	12.02	11.19	non-financial indicators				
	0	53	5.06	23.29		0	53	6.91	3.19					
X2	1	53	1.02	0.21	X8	1	53	0.04	0.06	C1	1	53	33.37	14.74
	0	53	0.95	0.21		0	53	0.04	0.03		0	53	30.28	12.37
X3	1	53	8.96	5.89	X9	1	53	0.55	1.35	C2	1	53	0.45	0.50
X3	0	53	15.66	18.47		0	53	0.33	0.62		0	53	0.42	0.50
X4	1	53	2.48	9.88	X10	1	53	-5.31	29.34	C3	1	53	0.39	0.07
	0	53	-2.03	18.92		0	53	0.71	0.47		0	53	0.37	0.04
X5	1	53	[illegible]	[illegible]	X11	1	53	[illegible]	[illegible]	C4	1	53	[illegible]	0.19
	0	53	0.02	0.02		0	53	0.46	3.28		0	53	0.91	0.30
X6	1	53	[illegible]	[illegible]	X12	1	53	[illegible]	[illegible]	C5	1	53	[illegible]	[illegible]
	0	53	-0.42	[illegible]		0	53	[illegible]	[illegible]		0	53	[illegible]	[illegible]

Note: St. Dev – Standard Deviations; 1 – means company with fraud; 0 – means the company without fraud.

Considering the multi-collinear analysis results, the VIF of all variables is less than 10, which confirms no multi-collinearity in the regression model. Logistic regression results are shown in Tab. 2. Considering the findings, X3, X5, X7, X10, and C3 are significant at the 10% level, and the overall prediction accuracy of the model is 83%. The values of indicators of the model's fit goodness (-2Log likelihood, Cox&Snell R2 and Nagelkerke R2) are 82.506a, 0.456 and 0.607, respectively.

Table 2 The outputs of logistic regression

Variable	Coeff.	St. Er.	Variable	Coeff.	St. Er.	Variable	Coeff.
X1	-0.01	0.06	0.93	X10	-1.06	0.41	0.01
X2	0.65	1.47	0.66	X11	0.00	0.13	1.00
X3	-0.10	0.05	0.05	X12	-0.44	0.34	0.20
X4	0.02	0.04	0.60	C1	0.03	0.02	0.17
X5	24.03	13.15	0.07	C2	-0.24	0.60	0.69
X6	0.04	0.06	0.54	C3	10.20	5.42	0.06
X7	0.13	0.08	0.10	C4	1.98	2.04	0.33
X8	-3.19	7.59	0.67	C5	0.41	1.77	0.82
X9	0.27	0.30	0.36	const.	-7.80	3.38	0.02
-2 Log likelihood							82.506a
Cox&Snell R2							0.46
Nagelkerke R2							0.61

The coefficient of X3 is negative, according to other studies. A smaller percentage of bad debt provision indicates a higher likelihood of fraud, assuming all other factors stay the same. Based on this, businesses are more inclined to reduce their bad debt provision in order to artificially boost earnings. Also positive is the coefficient for X5. Note that the possibility of

fraud increases with inventory proportion fall provision levels. During this time, businesses are more likely to remove large-scale inventory pricing provisions. The likelihood of fraud increases as the capitalization of interest under construction values rise (X7 is positive). It shows that businesses might use cost capitalization to artificially lower expenses. Since the cash collected from investment income has been declining quickly, X10 is negative. It might also be a sign of fraud.
Tab. 4 displays the model (13)'s recognition effect findings. Overall, the model's prediction accuracy is 83%, which is greater than previous research (He & Gao, 2020; Wang, 2020; Li et al., 2015). According to the results, there is a comparative advantage in accurately judging fraud when using the created multi-relationship-based fraud identification model.

Table 3 The results of logistic accuracy statistics of regression

Classify		Engage in Embezzlement		Precision %
Engage in Embezzlement	0	45	8	84.9
	1	10	43	81.1
Overall Percentage				83
Logistic accuracy statistics of regression in the existing literature				
The Literature Name	Number of Indi-cators	Precision %		
He & Gao (2020)	27	79.8		
Wang (2020)	25	80.46		
Li et al. (2015)	17	70.6		

The fresh control samples are created using the one-to-one matching approach in order to verify the accuracy and dependability of the results. There are 100 fraudulent and nonfraudulent firms in the new collection. Tab. 5 presents significant results at the 10% level for X7, X8, X10, X12, and C3. The model's overall prediction accuracy is 92%. X10 and X12 have negative regression coefficients, while X7 and X8 have positive ones.

Table 4 The findings of the robustness test

Variable	Coeff.	St. Er.	Variable	Coeff.	St. Er.	Variable	Coeff.
X1	0.12	0.11	0.93	X10	-1.29	0.47	0.01
X2	0.46	2.98	0.66	X11	-2.25	2.15	0.30
X3	-0.08	0.07	0.05	X12	-1.88	1.04	0.07
X4	-0.01	0.05	0.60	C1	-0.03	0.04	0.37
X5	7.72	11.36	0.07	C2	1.19	0.98	0.22
X6	0.04	0.17	0.54	C3	21.35	8.53	0.01
X7	0.67	0.20	0.10	C4	-3.33	7.03	0.64
X8	22.93	13.40	0.67	C5	8.11	5.72	0.16
X9	-0.38	0.34	0.36	const.	-17.38	7.69	0.02
-2 Log likelihood							40.235a
Cox&Snell R2							0.63
Nagelkerke R2							0.84

Thus, taking into account the results in Tab. 5 and keeping the other factors constant, the following circumstances demonstrate the likelihood of fraud:
X7: the increase in the interest capitalization amount of the ongoing project increases the likelihood of fraud, suggesting that the business may inadvertently lower costs through cost capitalization; X8: the likelihood of fraud increases with the ratio of the balance of ongoing projects to total assets. It suggests that businesses might deceitfully lower expenses by postponing turning ongoing initiatives into fixed assets; X10: The likelihood of fraud increases with decreasing cash earned from investment income. It suggests that the company might act as though it is a fraudulent foreign investment transferring assets; X12: the likelihood of fraud increases with a decrease in the ratio of the net increase in cash and cash equivalents to the change in monetary funds, indicating that more substantial funds are being used by fraudulent enterprises. The empirical findings in Tab. 5 demonstrate that the model's overall prediction accuracy is 92%, which is similar to Tab. 4's results.

Table 5 The results of overall prediction accuracy for robust model

Classify		Engage in Embezzlement		Precision %
		0	1	
Engage in Embezzlement	0	48	2	96
	1	6	44	88
Overall Percentage				92

The majority of multi-connection indicators do not make it into the regression model with the thorough analysis, but this does not mean that the tick relationship indicators are unnecessary. Not every fraud company will use the same fraud techniques, as was previously indicated. The empirical fraud samples and a portion of the normal samples do not, therefore, differ significantly. The rationality of the index system extracted in this research is unaffected by their exclusion from the regression model. Alternatively, a different viewpoint demonstrates the variety of corporate deception practices and the traits of identification challenges.

CONCLUSION

This study examines the link between statement items as a basis for feature extraction in enterprise financial fraud identification. Twelve indicators are created, and five non-financial indicators are chosen to detect financial fraud based on the categorization of firm operations and the connections between the three main financial statements. The findings demonstrate that the constructed model has an overall prediction accuracy of 83%, and the results of the robustness test further substantiate the method's efficacy and reasonableness. The multi-relationship index can increase the accuracy of fraud recognition, according to the empirical data. This work adds to the body of pertinent research on the choice of index system for identifying financial fraud. Stakeholders in the organization might use the suggested fraud identification technique to increase the technical degree of efficiency in financial fraud identification. Notwithstanding the noteworthy outcomes, there are several constraints with the study. Accurate sample compilation is needed for analysis when employing Machine Learning algorithms for fraud detection through the use of logistic regression. It is possible to assign the anomalies from a probability viewpoint if the fraudulent operations are not discovered and are taken into account as typical businesses for empirical study. In addition, larger studied samples have to be used for additional research in order to get more precise results. It should be mentioned that one element that contributes to financial fraud is knowledge asymmetry. In this instance, it ought to be taken into account in additional research. Furthermore, financial fraud has a big influence on how appealing the firms are to investors, which is something that future investigations should take into account.

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