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Factors affecting the detection of fraud in financial statements using structural equation modeling

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Abstract

The costs of fraud, both socially and financially, affect citizenship trust. The shadow of such distrust lies on the stock exchange and other investment institutions, and it will take a long way to get out of this dreadful shadow. Therefore, considering the importance and significant costs of financial fraud, this study seeks to predict fraud in financial statements using court accounting components. The statistical population includes three groups of accounting professions (official expert of justice in the field of accounting and auditing, auditors and financial managers of Tehran province), academics (all universities in Tehran province that have accounting and law), law and jurisprudence (lawyers and judges) is in Tehran province. Due to the infinity of the population, with the help of Cochran's formula, the sample size was 384 people. The results of structural equation method showed that each of the variables of essential traits of court accountants, basic skills of court accountants, advanced skills of court accountants and Islamic moral values of court accountants have a positive and significant effect on fraud detection.

Keywords: Fraud detection, financial statements, forensic accounting, structural equations
2020 MSC: 91G80

1 Introduction

Every year in developed countries, financial fraud accounts for seven percent of government and private sector revenues [11]. The situation is much worse in developing countries and emerging markets. According to research, fraudsters in these countries are estimated to plunder 12 to 15 percent of public and private sector revenues [5]. In developed countries, however, only 40 percent of fraud is detected, and the share of fraud detected in developing countries is less than 15 percent, with only a small share of recoverable fraud losses. Fraud is not a rare phenomenon or a phenomenon that only occurs in other companies. Although it is difficult to determine the exact amount of fraudulent losses (part of which is due to undetected fraud), most organizations lose between 0.05 and 2 percent of their revenue through fraudulent actions by employees, vendors, and others. Give. A KPMG Judicial Services Division survey found that employees are responsible for 60 percent of fraudulent losses [3]. A 1997 report by the Association of Formal Fraud Investigators states that fraud losses account for 6% of gross domestic product. A 1997 study by the Deloitte and Tashe Institute found that international fraud across the EU cost the EU 60 billion a year. A 2003 World Economic Crime Survey by the Price Water Houscopers Accounting Institute found that 37 percent of

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companies worldwide were victims of fraud in the past two years, losing an average of $ 2 million [8]. The functional nature of accounting information is to reduce ambiguity in users' decisions. This information must be useful in the decision-making process, and usefulness requires both relevance and reliability. Since this information is provided with the opinion and responsibility of the company's management, they cannot meet the different needs of users with acceptable neutrality and confidence. Many personal estimates, judgments, and opinions are also applied to the process of identifying, measuring, and reporting information. Therefore, these forms cannot be free from intentional errors or distortions [12].

In recent years, after the revelation of the financial and accounting scandals of the big companies of the western world such as Enron, Wordcom, Xerox and Merck, it became clear that the managers of these companies have been drawing better faces for many years. Due to this, fundamental doubts have been raised about the "quality" and "transparency" of accounting and auditing information [6]. In Iran, due to the expansion of the size and number of public joint stock companies and, consequently, the increase in users of accounting information, the accounting and auditing profession should increase the quality of its work in line with society's expectations [4].

The Code of Conduct obliges auditors and accountants to be honest and trustworthy in all areas of their profession. Auditors are required to comply with auditing standards to plan and execute all their operations with skepticism and not to be indifferent to issues that may be the source of corruption and fraud [1].

The issue of fraud, bankruptcy and corporate failure has always been a complex and noteworthy issue. In the present world, the unlimited human desires and aspirations are confronted with limited economic resources [15]. The rise and fall of any phenomenon is rooted in the real and logical needs of human societies. The emergence of fraud auditing in the field of professional services cannot be an exception to this rule. Nowadays, technological advances and extensive changes in the business environment have led to increasing acceleration in the economy, and due to the increasing competition of institutions, the achievement of the expected income is limited, so the incidence of fraud is increasing day by day [16].

The increasing number of frauds, distortions and re-submissions, often compounded by the bankruptcy of large corporations, has raised concerns about the quality of financial statements [2]. Therefore, the prevention or detection of significant errors and distortions in the financial statements has always been the focus of investors, legislators, managers and auditors, and accordingly, various standards and guidelines on the responsibility of auditors in detecting fraud. And distortions have been made in the financial statements [13].

In Iran, due to the increase in the number of companies listed on the stock exchange and the process of privatization and capital growth and the need for public release of financial statements; Predict the possibility of financial statement fraud in the disclosure of financial information in methods other than routine audits due to audit limitations; It is a necessity and it is of special importance. So that ignoring it may on the one hand cause irreparable damage to the accounting and auditing profession and on the other hand cause loss of public trust and hurt investors and ultimately cause an economic crisis in society at the macro level. In our country (Iran) there is no institution to directly investigate and detect cases of possible fraud and also no information base to report such cases. Institutions such as the Securities and Exchange Commission do not disclose information about any misstatements, particularly financial statements, to the public and analysts. The only cases that are pursued in the stock exchange organization are the possibility of fraud by the holders of confidential information (especially managers) in these companies and in case of issuing a verdict through the courts; Items are notified privately. Lack of research studies in this field is another significant limitation. What draws everyone to fraud and misconduct are the costs that fraud imposes on society. The costs of fraud, both socially and financially, affect citizenship trust. The shadow of such distrust is placed on the stock exchange and other investment institutions, and it will be a long way to get out of this dreadful shadow. Therefore, this study, considering the importance and significant costs of financial fraud, seeks the factors affecting fraudulent financial reporting using structural equation modeling.

2 Research Methodology

2.1 Research Method

This study is pseudo-experimental. In pseudo-experimental research, the researcher has no control over the process of data creation and it can't define different groups, such as the experimental and control group, but, the whole group plays the role of the experimental group. The present study, in terms of results, applied; in terms of purpose, analytical; in terms of the logic of execution, a combination of analogy and induction; in terms of the execution process, quantitative and in terms of time period, it's cross-sectional.

2.2 Population and Statistical Sample

The statistical population of the study includes three groups of accounting profession (official expert of justice in the field of accounting and auditing, auditors and financial managers of Tehran province), academics (all universities in Tehran province that have accounting and law), law and jurisprudence (lawyers and Judges) is in Tehran province. The statistical sample according to Cochran's formula was 384 people.

2.3 Mathematical model and the method of data analysis

The following equation are used to test research hypotheses:

$$DF_i = \beta_0 + \beta_1 ET_i + \beta_1 BS_i + \beta_1 AS_i + \beta_1 IMV_i + \varepsilon_i \tag{2.1}$$

In the above equations: DF: Discover fraud, ET: Essential traits, BS: Basic skills, AS: Advanced skills, IMV: Islamic moral values.

Considering that in the present research, the relation between variables have been studied in the framework of a scientific model, statistical inference were analyzed by structural equation modeling using AMOS software. Also, evaluated the fit of the proposed pattern based on the Chi-squared index (x^2), Comparative Fit Index (CFI), goodness of fit index (GFI), Adjusted goodness of fit index (AGFI) and Root Mean Square Error of Approximation (RMSEA). In order to fit the pattern, it is essential that these indexes have the necessary standards. If the index (X^2/df) be smaller than 3 and the amount of (rmsea) be smaller and closer to zero and fitting indexes (cfi,gfi,agfi) be closer to 1, it indicates that the proposed model has been confirmed.

The AMOS framework can be summarized into three matrix equations, two for the measurement model component and one for the path model component. For the measurement model component,

$$X = \Lambda_x \xi + \delta \tag{2.2}$$

$$Y = \Lambda_x \eta + \delta \tag{2.3}$$

where x is a $p \times 1$ vector of observed exogenous variables, and it is a linear function of a $j \times 1$ vector of exogenous latent variables ξ and a $p \times 1$ vector of measurement error δ. Λ_x is a $p \times j$ matrix of factor loadings relating x to ξ. Similarly, y is a $q \times 1$ vector of observed endogenous variables, η is a $k \times 1$ vector of endogenous latent variables, ε is a $q \times 1$ vector of measurement error for the endogenous variables, and Λ_y is a $q \times k$ matrix of factor loadings relating y to η. Associated with (2.2) and (2.3), respectively, are two variance-covariance matrices, $\Theta\delta$ and $\Theta\varepsilon$. The matrix $\Theta\delta$ is a $p \times p$ matrix of variances and covariances among measurement errors δ, and $\Theta\varepsilon$ is a $q \times q$ matrix of variances and covariances among measurement errors ε. For flexibility, AMOS describes the path model component as relationships among latent variables,

$$\eta = B\eta + \Gamma\xi + \zeta \tag{2.4}$$

where B is a $k \times k$ matrix of path coefficients describing the relationships among endogenous latent variables, Γ is a $k \times j$ matrix of path coefficients describing the linear effects of exogenous variables on endogenous variables, and ζ is a $k \times 1$ vector of errors of endogenous variables. Associated with (2.4) are two variance-covariance matrices: Φ is a $j \times j$ variance-covariance matrix of latent exogenous variables, and Ψ is a $k \times k$ matrix of covariances among errors of endogenous variables. With only these three equations, AMOS is a flexible mathematical framework that can accommodate any specification of a SEM model. SEM has been typically implemented through covariance structure modeling where the variance-covariance matrix is the basic statistic for modeling. Model fitting is based on a fitting function that minimizes the difference between the model-implied variance-covariance matrix $\sum$ and the observed variance-covariance matrix S,

$$\min f(\sum, S) \tag{2.5}$$

where S is estimated from observed data, $\sum$ is predicted from the causal and noncausal associations specified in the model, and $f(\sum, S)$ is a generic function of the difference between $\sum$ and S based on an estimation method that follows. As Shipley concisely stated, causation implies correlation; that is, if there is a causal relationship between

two variables, there must exist a systematic relationship between them. Hence, by specifying a set of theoretical causal paths, one can reconstruct the model-implied variance-covariance matrix $\sum$ from total effects and unanalyzed associations. Hayduk outlined a step-by-step formulation under the AMOS mathematical framework, specifying the following mathematical equation for $\sum$:

$$\sum = \begin{bmatrix} \Lambda_y A(\Gamma\Phi\acute{\Gamma} + \Psi)A''\acute{A}_y\Theta_\varepsilon & \Lambda_y A\Gamma\Phi\acute{A}_x \\ \Lambda_x\Phi\acute{\Gamma}A\acute{y} & \Lambda_x\Phi A_x\acute{+}\Theta_\delta \end{bmatrix} \tag{2.6}$$

where $A = (I-B)^{-1}$. Note that in (2.6) the derivation of $\sum$ does not involve the observed and latent exogenous and endogenous variables (i.e., x, y, ξ, and η). A common method in SEM for estimating parameters in $\sum$ is maximum likelihood (ML). In ML estimation, the algorithm iteratively searches for a set of parameter values that minimizes the deviations between elements of S and $\sum$. This minimization is accomplished by deriving a fitting function $f(\sum, S)$ (2.5) based on the logarithm of a likelihood ratio, where the ratio is the likelihood of a given fitted model to the likelihood of a perfectly fitting model. The maximum likelihood procedure requires the endogenous variables to follow a multivariate normal (MVN) distribution, and S to follow a Wishart distribution. Hayduk described the steps in the derivation and expressed the fitting function FML as

$$F_{ML} = \log|\sum| + tr(S\sum^{-1}) - \log|S| + tr(SS^{-1}) \tag{2.7}$$

where $tr()$ refers to the trace of a matrix and $\sum$ and S are defined as above. Proper application of (2.7) also requires that observations are independently and identically distributed and that matrices $\sum$ and S are positive definite. After minimizing (2.7) through an iterative process of parameter estimation, the final results are the estimated variance-covariance matrices and path coefficients for the specified model. The first is the overall model chi-square test based on a test statistic that is a function of the mentioned fitting function FML (2.7) as follows:

$$X_M^2 = (n-1)F_{ML} \tag{2.8}$$

where n is sample size and X_M^2 follows a chi-square distribution with degree of freedom df_M as defined above. Subsequently, a P value is estimated and evaluated against a significance level. The overall model chi-square test is only applicable for an over-identified model, that is, when $df_M > 0$. A just identified model ($df_M = 0$), for example, a path model representation of a multiple regression, does not have the required degrees of freedom for model testing.

The second fit statistic to consider is the Root Mean Square Error of Approximation (RMSEA), which is parsimony-adjusted index that accounts for model complexity. The index approximates a noncentral chi-square distribution with the estimated noncentrality parameter as

$$\hat{\delta}_M = \max(X_M^2 - df_M, 0) \tag{2.9}$$

where X_M^2 is computed from (2.8) and df_M is defined above. The magnitude of $\hat{\delta}_M$ reflects the degree of misspecification of the fitted model. The RMSEA is then defined as

$$RMSEA = \sqrt{\frac{\hat{\delta}_M}{(n-1)df_M}} \tag{2.10}$$

Lastly, the Joreskog-Sorbom Goodness of Fit Index (GFI) is a measure of relative amount of variances and covariances jointly accounted for by the model, and it is defined as

$$GFI = 1 - \frac{tr(\sum^{-1} S - 1)^2}{tr(\sum^{-1} S)^2} \tag{2.11}$$

where I is identity matrix. GFI ranged from 0 to 1.0 with 1.0 indicating the best fit. Considering that the number of free parameters in SEM is much smaller than that in EFA when m is large, Yuan [17] proposed to replace $(N-1)$ in the definition of T_{ml} with $N_y = N - (2p+13)/6 - m/3$. However, this proposal is only a heuristic rather than one that is statistically justified. A more complicated correction was originally offered by Swain [14], who proposed to replace $(N-1)$ in T_{ml} by

$$N_8 = \frac{N - 1[p(2p^2 + 3p - 1) - h_q(2h_q^2 + 3h_q - 1)]}{12df} \tag{2.12}$$

Where $h_q = (1 + 8q)^{\frac{1}{2}}/2$ and q is the number of free parameters in the structural model. Studies by Fouladi [7], Herzog et al. [9] and Herzog and Boomsma [10] indicate that the performance of test from best to worst are $T_{mls} = N_s F_{ml}, T_{mly} = N_y F_{ml}$, and T_{mlb}. Although the performance of T_{mls} is potentially promising, the correction is not statistically justified.

3 Statistical Findings

3.1 Checking the normality of data distribution

To evaluate the normality of the distribution of the main variables, the valid Kolmogorov-Smirnov test is used. In interpreting the test results, if the observed error level more than 0.05, in that case, the observed distribution is the same as the theoretical distribution and there is no difference between them. That is, the obtained distribution is normal distribution.

Table 1: Variables Normality Test

Variable	Sig	Result
Discover fraud (F1)	0.163	Normal
Essential traits (F2)	0.135	Normal
Basic skills (F3)	0.149	Normal
Advanced skills (F4)	0.097	Normal
Islamic moral values (F5)	0.179	Normal

According to the values obtained from Smirnov-Kolmogorov statistics (table 1), it can be inferred that the expected distribution is not significantly different from the observed distribution for all variables and so the distribution of these variables is normal.

3.2 Factor analysis

In this research, to identify and measure the latent variables, confirmatory factor analysis has been used. In performing the factor analysis, we must first be sure to use the available data that is required for analysis, to ensure this, the KMO index is used. By using this test, we can ensure the adequacy of sampling. This index is in the range of 0 to 1, if the index value is close to one, the desired data are suitable for factor analysis and otherwise, the results of factor analysis are not suitable for the desired data.

Table 2: Results of KMO index and Bartlett's test of structures of research variables

Sampling adequacy ratio coefficient KMW		**0.419**
Bartlett's test	Chi-square test	953.3159
	Degrees of freedom	214
	Sig	0.000

According to the above results, the amount of sampling adequacy for research structures is 0.419. Therefore, the sample size is appropriate for using structural equations. Generally, high values (close to 1) show that factor analysis is applicable to data. If this value is less than 0.5, the results of factor analysis probably will not be useful for the data. Also, Bartlett's Test of Sphericity is significant (because its significance level is less than the test level), so, the relation between variables or their covariance matrix is suitable for factor analysis.

3.3 Fitting structural model and hypotheses Test

Figure 1 shows the research structural model in which the estimated regression coefficients between the variables of research structural model are displayed.

The summary of the results of fitting the research structural model is shown in the table below.

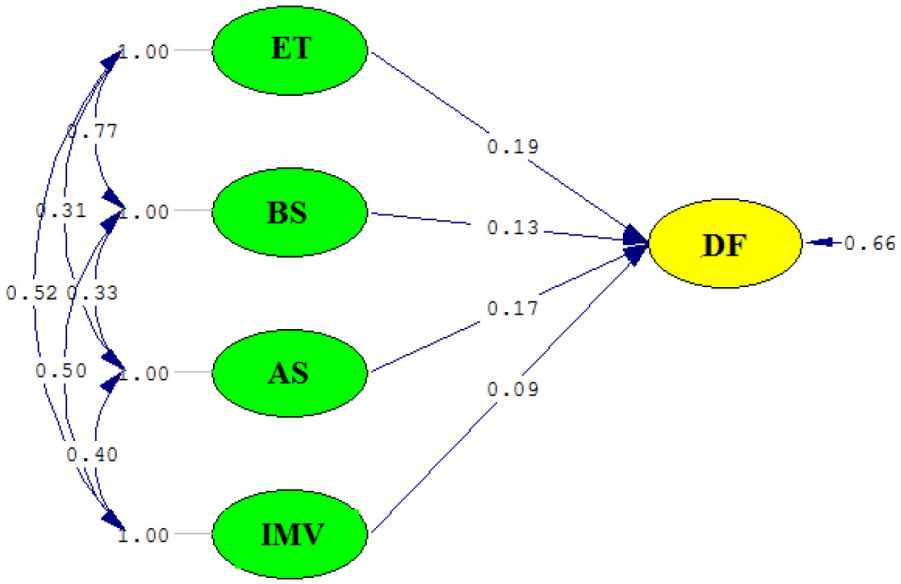

Figure 1: values of Standard coefficients of relations between research model variables in structural model

Table 3: Fitting indexes for the proposed model

Grouping indicators	indicators	Initial Model	Acceptable fit
Absolute fit indicators	GFI	0.921	$GFI > 90\%$
	RMR	0.939	$RMR > 90\%$
Comparative fit indices	TLI	0.927	$TLI > 90\%$
	NFI	0.905	$NFI > 90\%$
	CFI	0.038	$CFI > 90\%$
	IFI	0.952	$IFI > 90\%$
Affordable fitting indices	PNFI	0.841	$PNFI > 50\%$
	PCFI	0.826	$PCFI > 50\%$
	RMSEA	0.043	$RMSEA < 5\%$

Table 4: The results of fitting the research structural model

Relationships between concepts and indicators in the model	Standard coefficient	Test statistics	Sig
The effect of essential traits of court accountants on fraud detection	0.19	5.39	0.000
The effect of basic skills of court accountants on fraud detection	0.13	9.21	0.000
The effect of advanced skills of court accountants on fraud detection	0.17	6.09	0.036
The effect of Islamic moral values of court accountants on fraud detection	0.09	8.16	0.000

As shown in Table 3, all fitted indexes of the model are at the desired level.

According to the coefficients of Table 4, the mathematical equations of the research are rewritten as follows:

$$DF_i = 0.57 + 0.19ET_i + 0.13BS_i + 0.17AS_i + 0.09IMV_i + \varepsilon_i \tag{3.1}$$

Given that the value of the student's statistic is greater than 1.96; The essential traits of court accountants, basic skills of court accountants, advanced skills of court accountants and Islamic ethical values of court accountants have a significant relationship with the detection of fraud. In other words, the characteristics of essential traits, basic skills, advanced skills and Islamic moral values of court accountants have a significant effect on the detection of fraud.

4 Conclusion and Research Suggestions

One of the effective factors in reducing the reliability of financial reports and statements is the phenomenon of fraud, which increases the risk and cost of business, reduces the trust of investors and calls into question the credibility and integrity of the accounting profession. Given the importance of fraud in the economy and the huge losses it entails for shareholders and society, and that many financial frauds are not detected or disclosed for any reason, and also in general in Iran, unlike in developed countries where the organization To detect financial fraud, there are no institutions and organizations and documented information about fraud, so in this study, an attempt was made to examine the factors affecting fraudulent financial reporting in order to predict fraud. The results of structural equation method showed that each of the variables of essential traits of court accountants, basic skills of court accountants, advanced skills of court accountants and Islamic ethical values of court accountants have a positive and significant effect on fraud detection.

Findings showed that various factors are effective in committing fraud. Therefore, in order to be effective in controlling fraud, it is suggested that the underlying conditions, which include public culture and economic, religious and legal factors, be amended by each of the responsible authorities. It is also suggested that company managers can play an important role in preventing fraud in order to reduce costs and achieve organizational goals by spreading organizational ethics and effective control systems. In order for the managers of their company to be committed to honesty and integrity, the employees will also carry out their duties in this direction. Supervisory organizations such as the Securities and Exchange Commission and the auditing organization can play a role by applying appropriate and efficient rules, standards and instructions so that these rules are transparent and expressive and cannot be violated by companies and managers. Play an important role in cheating.

According to the characteristics of essential traits, it is suggested that by creating an organizational culture to preserve moral and Islamic values and creating organizational justice for job satisfaction, court accountants should be motivated to increase their organizational confidence and commitment accordingly.

Auditing skills have also been selected as the main basic skills, which shows the high importance of auditing techniques, which is one of the important tools of the court accountant for research and investigation, and is recommended in view of the current auditing conditions that some institutions Auditors hire students and graduates for 6 months or even a year for internships without insurance and salary, and this has led to young people either not entering the profession or part-time due to these difficult conditions. Leaving the solution, it is necessary to make arrangements to facilitate the entry of students and graduates into the auditing profession to gain experience, strengthen basic skills and increase their knowledge of accounting standards, auditing and tax law.

Due to the limited activities of court accountants in Iran, by expanding the skill level of court accountants, the scope of their activities can be expanded to be synchronized with the profession of court accountant in the world. Encouraging court accountants to obtain international professional qualifications and test their knowledge and expertise in international examinations, such as obtaining a certified public accountant degree, can benefit in synchronizing and updating the knowledge and strengthening of court accountants.

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