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DETECTION AND PREDICTION OF MANAGERIAL FRAUD IN THE FINANCIAL STATEMENTS OF TUNISIAN BANKS

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ABSTRACT

This article models the detection and prediction of managerial fraud in the financial statements of Tunisian banks. The methodology used consist of examining a battery of financial ratios used by the Federal Deposit Insurance Corporation (FDIC) as indicators of the financial situation of a bank. We test the predictive power of these ratios using logistic regression. The results show that we can detect managerial fraud in the financial statements of Tunisian banks using performance ratios three years before its occurrence with a classification rate of 71.1%.

JEL: M41, M42, C23, C25, G21

KEYWORDS: Fraud, Ratio, Financial Statements, Bank, Detection, Prevention, Logistic Regression Model

INTRODUCTION

Garner (2009) defines fraud as "A knowing misrepresentation of the truth or concealment of a material fact to induce another to act to his or her detriment". The professional and academic literature defines fraud in financial statements differently. The International Federation of Accountants (IFAC) devoted an entire standard for auditor responsibility relating to fraud. The International Standard on Auditing (ISA) 240 (IFAC (2009)) defines fraud as "an intentional act by one or more individuals among management, those charged with governance, employees, or third parties, involving the use of deception to obtain an unjust or illegal advantage".

Moreover, the American Institute of Certified Public Accountants (AICPA) in the Statement on Auditing Standard (SAS) N°99 -Consideration of Fraud in a Financial Statement Audit- refers to fraud as "an intentional act that results in a material misstatement of financial statements that are the subject of an audit". In the SAS 99, two types of fraud are considered. The first type are misstatements arising from fraudulent financial reporting such as falsification of accounting records or intentional omission from the financial statements of events, transactions, or other significant information. The second are misstatements arising from misappropriation of assets such as theft of assets, embezzling receipts or causing an entity to pay for goods or services not received.

The results of the latest report published by the Association of Certified Fraud Examiners (ACFE) in 2012 are alarming. Indeed, the lighthouse observation of this report is that fraud costs 5% of total annual turnover of the companies affected. The Committee of Sponsoring Organizations of the Treadway Commission (COSO), in its third report published in 2010 showed that for a sample of 347 fraudulent companies, the median fraud is $12.1 million. For 30 cases of fraud, each case includes anomalies or misappropriation of $500 million or more.

The study of fraud in financial statements of public companies in Tunisia is especially needed after the revolution. Cases of fraudulent financial reporting, misappropriation of assets or embezzlement, have been in the courts. This study focuses on Tunisian banks since the banking sector had been subject to misuse of funds in the form of granting large credits for projects without securing them or at an interest rate lower than it should be. This remainder of the paper proceeds as follows. Section 2 presents a brief review of literature and the hypothesis. Section 3 presents the methodology. Section 4 presents the results. Section 5 concludes.

LITERATURE REVIEW AND HYPOTHESIS

Motivations for companies to commit financial statements fraud are numerous. Economic incentives are common causes of fraud in the financial statements, as well as psychotic motivations, self-centeredness and ideology. These motivations can play an important role in financial statement fraud. Pressures and economic incentives to match analysts' forecasts are fundamental motivations for listed companies to commit financial fraud. Psychological motivations associated with criminal behavior are rare in our case. Egocentric motivations are outlined in the fact that, through fraud, the person increases his personal prestige. The desire of managers to fulfill a functional authority in society results in this type of motivation. Ideological motivations encourage executives to think that, through fraud, they can become market leaders and consequently, improve their position in society. Managerial fraud and companies' performance have been separated, each having its own theoretical framework. According to Griffin & Lopez, the research of management illegal behavior had produced a variety of models and definitions.

Fraud in the financial statements occurs, if the company has strong incentives, as well as economic reasons to announce a more favorable financial performance than actually occurred, in accordance with Generally Accepted Accounting Principles (GAAP). Empirical investigations (Carter & Stover (1991); Latham & Jacobs, (2000a, 2000b)) identified two fundamental variables, managerial ownership and the debt limit, which affect the extent of fraud in financial statements. These studies show that when managerial ownership is between 5-25%, opportunistic behavior of managers is expected and the likelihood of engaging in financial statement fraud is higher. Previous research (Carcello & Palmrose (1994); Dechow et al. (1996); Lys & Watts (1994)) focused on examining measures of financial difficulties in terms of weak financial conditions and weak financial performance as motivational mechanisms. The conclusions reached by this research, argue that motivations to commit fraud in the financial statements increases when firm encounter financial difficulties. The researchers found the chance to engage in financial statements fraud increase when company financial conditions and performance deteriorate.

According to the COSO Report (2010), the Securities and Exchange Commission (SEC) provided discussion in Accounting and Auditing Enforcement Releases (AAERs) about the alleged motivation for fraud. Most commonly cited reasons summarized by the SEC in the AAERs include committing the fraud to 1.) Meet external earnings expectations of analysts and others, 2.) Meet internally set financial targets or make the company look better, 3.) Conceal the company's deteriorating financial condition, 4.) Increase the stock price, 5.) Bolster financial position for pending equity or debt financing, 6.) Increase management compensation through achievement of bonus targets and through enhanced stock appreciation and 7.) Cover up assets misappropriated for personal gain.

Recent corporate governance scandals show that in most companies, executives have incentives to increase profits to improve their bonuses. Giving shareholders authority to choose elements of bonuses to executives can eliminate these incentives. Zahra et al. (2005) found that fraudulent behaviors in various disciplines have generated different perspectives and labels.

Studies developed on bank financial statements fraud are rare. The 2012 report of the ACFE shows that banking and financial services are leading victims by generating 16.7% of fraud cases. Moreover, the report

shows that managerial fraud ranks first and second in the ranking of fraudsters. Indeed, there is a strong correlation between the fraudster function within the company and the losses caused by the fraud. The median loss caused by the owner/manager is more than three times the loss caused by managers, and more than nine times the losses caused by employees. Ramage et al. (1979) noted that financial institutions have different characteristics of errors than other sectors. Palmrose (1988) and St. Pierre & Anderson (1984) showed that about 30% of trials involved banks and loan institutions auditors. Kreutzfeldt & Wallace (1986, 1990) noted that characteristics of inaccuracies, in terms of error rate and false accounts, vary across sectors. Banks are exposed to significantly higher error rates than other sector companies in liquidity accounts. Maletta & Wright (1996) examined 36 commercial banks and 14 savings and loan institutions (S&Ls). S&Ls have the highest error percentage that overstated net income of about 68.8%.

Abaoub et al. (2012) studied banking sector fraud in the Tunisian context. They choose a subset of financial ratios used by the Federal Deposit Insurance Corporation as indicators of the financial situation of a U.S. bank and tested their predictive power three years before the occurrence of fraud. In their research, Abaoub et al. (2012) analyzed the mean difference for the group of fraudulent banks and the group of non-fraudulent banks. This allowed the determination, for each period, of the most significant ratios in fraud detection. In a second stage, the authors performed discriminant analysis, which showed that fraud could be detected two years before its occurrence. Next, we follow present our empirical validation for Tunisian banks. The assumptions are classified into three groups, depending on the nature of ratios:

Assumption relating to performance ratios H1
$H1_1$: Banks with low performance ratios are exposed to a greater occurrence of managerial fraud.

Assumption about growth ratios H2
$H2_1$: Banks with high growth ratios are exposed to a greater occurrence of managerial fraud.

Assumptions regarding capital ratios H3
$H3_1$: Banks with low capital ratios are exposed to an increased frequency of managerial fraud.

METHODOLOGY

The objective of this study is to detect managerial fraud before its occurrence. We test the predictive ability of a battery of ratios, one year, two years and three years before the occurrence of fraud. Different techniques have been developed to detect financial statement fraud (Ravisankar et al. (2011)). However, in this paper, we adopt the McAteer methodology (2009). This choice is based on several arguments. In addition to the scarcity of studies on the detection and prevention of fraud in banks financial statements, McAteer's methodology uses three groups of financial ratios produced by the Federal Deposit Insurance Corporation (FDIC). According to King et al. (2005), the FDIC uses financial ratios, among others indicators, as part of their responsibilities in the surveillance and monitoring activities of banks to ensure bank safety and soundness. Table 1 presents detail of the ratios used in our study. This methodology is based primarily on fraud prevention. So, there is a concern for the prediction-detection and prevention of fraud, an issue that seems relevant in regards to the risk of banks failure. The period chosen is based on the year of fraud. The period generally extends from 1999 to 2010. For our analysis, we took into account a three-year period prior to the occurrence of fraud for fraudulent and non-fraudulent banks. We consider that a bank commits fraud when the Financial Market Council (the Tunisian equivalent of the SEC) or the Government Accountability Office announced the occurrence of fraud or its external auditors issued an adverse opinion to the financial statements.

Data were collected directly from the web sites of banks or from the printed annual reports available at the library of Central Bank of Tunisia (BCT). The sample consists of 10 Tunisian universal banks over a period

of 12 Years. Table 2 provides descriptive statistics of the sample chosen, including the number of observation, the minimum, the maximum, the mean and the standard deviation of each variable.

Table 1: Variables in the Study

Variable	Definition
Performance ratios	
V_1 (ASTEMPM)	Assets per employee
V_2 (EEFFR)	Efficiency ratio
V_3 (IDDIVNIR)	Cash dividends to net income
V_4 (IDLNCORR)	Net loans and leases to core deposit
V_5 (INATRESSR)	Loss allowance to loans
V_6 (INLSDEPR)	Net loans and leases to deposits
V_7 (INTEXPY)	Cost of funding assets
V_8 (INTINCY)	Yield on earning assets
V_9 (NIMY)	Net interest margin
V_{10} (NOIJY)	Net operating income to assets
V_{11} (NONIIY)	Noninterest income to earning assets
V_{12} (NONIXY)	Noninterest expenses to earning assets
V_{13} (ROA)	Return on assets
V_{14} (ROE)	Return on equity
V_{15} (ROEEINJR)	Retained earnings to average equity
Growth ratios	
V_1 (ASTEMPM)	Assets per employee
V_{16} (EQV)	Equity capital to assets
V_{17} (ROLLPS5TA)	Growth ratio 1
Capital ratios	
V_{16} (EQV)	Equity capital to assets
V_{18} (RBC1AAJ)	Core capital (leverage) ratio

This table shows variables examined in this study.

Table 2: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Total Asset	120	902,862,000	6,753,589,000	2,802,904,145	1,461,116,459
Number of Employees	120	781	5,826	1,645.2	832.21
ASTEMPM	120	786,516	4,578,061	1,807,938	787,827
EEFFR	120	-0.0071	0.0403	0.0083	0.0069
IDDIVNIR	120	0.0000	349.90	3.303	31.908
IDLNCORR	120	0.7660	1.5238	1.125	0.1815
INATRESSR	120	-0.0012	0.1178	0.0142	0.0142
INLSDEPR	120	0.7660	34.629	1.806	3.943
INTEXPY	120	0.0175	0.0548	0.0310	0.0062
INTINCY	120	0.0584	0.1231	0.0807	0.0100
NIMY	120	0.0320	0.0787	0.0492	0.0102
NOIJY	120	-0.1027	0.0377	0.0101	0.0151
NONIIY	120	0.0097	0.0506	0.0209	0.0059
NONIXY	120	0.0000	0.0041	0.0008	0.0007
ROA	120	-0.1035	0.4349	0.0152	0.0546
ROE	120	-0.0281	9.423	0.1720	0.8533
ROEEINJR	120	0.0000	0.2977	0.0617	0.0484
ASTEMPM	120	786,516	4,578,063	1,807,938	787,827
EQV	120	0.0330	0.1748	0.0958	0.0287
ROLLPS5TA	120	0.5168	0.9568	0.8502	0.0693
EQV	120	0.0330	0.1748	0.0958	0.0287
RBC1AAJ	120	4.720	29.348	10.485	4.144
Valid N (listwise)	120				

This table shows descriptive statistics of the variables used in the study.

We conducted our empirical tests on a sample of 10 Tunisian universal banks, namely Attijari Bank (AT), Banque Internationale Arabe de Tunisie (BIAT), Banque Nationale Agricole (BNA) Tunisian Banking Company (STB), Banque de Tunisie (BT), Banque de l'Habitat (BH), Amen Bank (AB), Arab Tunisian Bank (ATB), Union Internationale de Banques (UIB) and Union Bank for Trade and Industry (UBCI). The sample of fraudulent banks is composed of BIAT, BH, BNA, STB, UIB, AB, and AT. This means that each bank perpetrated at least one fraud in one year. The control group is composed of the remaining three banks namely BT, ATB and UBCI. Table 3 details the banks that committed fraud and those that did not during the period of the analysis of 1999 to 2010.

Table 3: Fraud Occurrence by Bank

Bank	Fraud	No Fraud
AB	x	
AT	x	
ATB		x
BH	x	
BIAT	x	
BNA	x	
BT		x
STB	x	
UIB	x	
UBCI		x

This table shows the existence of fraud occurrences by bank.

THE MODEL

The McAteer (2009) methodology is adapted to the Tunisian context. The dependent variable is a dichotomous variable equal to 1 (probability of 100%) for fraudulent banks and is equal to 0 for non-fraudulent banks (probability of 0%). The independent variables are 18 financial ratios out of 26 ratios produced by the FDIC. Some data are not available for all banks or for the entire period, such as the 'credit loss provision to net charge-offs', 'loan loss allowance to noncurrent loans', 'net charge-offs to loans', etc. These ratios are classified into three categories: performance ratios, growth ratios and capital ratios. Since the regression is to anticipate managerial fraud before its occurrence on several time intervals, the fraud model can be rewritten as follows:

$$Y = B_0 + B_1 X_{1(t-y)} + B_2 X_{2(t-y)} + \cdots + B_k X_{k(t-y)} + \varepsilon \quad (1)$$

Where Y is the probability of occurrence, B_0 is a constant and B_i are coefficients associated with the independent variables, X_i are the independent variables, t is the year of occurrence, y there is the interval in years, and ε is the model error. The list of the financial ratios (independent variables) are as identified in Table 1.

The use of the logistic regression completes the predictive aspect of the study. Logistic regression predicts or explains a nonparametric binary dependent variable by determining the probability of the independent variables that influence the dependent variable.

THE RESULTS

The examination of the correlation matrix presented in Table 4, allows us to conclude the existence of multicollinearity. However, Multicollinearity in regression coefficients does not affect the significance or validity of the model (Hair et al. (2006)). According to Kennedy (2008), a data set has multicollinearity if at least one simple correlation coefficient between the independent variables is at least 0.8 in absolute value.

Table 4. Correlation Matrix of the Independent Variables

	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9	V_{10}	V_{11}	V_{12}	V_{13}	V_{14}	V_{15}	V_{16}	V_{17}	V_{18}
V_1	1.000																	
V_2	.126	1.000																
V_3	-.077	-.091	1.000															
V_4	-.201	-.164	-.031	1.000														
V_5	-.083	-.176	-.051	-.212	1.000													
V_6	.207	.038	-.019	-.138	-.079	1.000												
V_7	.039	-.156	.015	-.073	.124	-.209	1.000											
V_8	-.264	-.272	-.085	-.170	.112	-.207	.253	1.000										
V_9	-.273	-.231	-.091	-.112	.022	-.084	-.262	**.844**	1.000									
V_{10}	.128	-.082	-.056	-.183	**-.829**	.024	-.052	.276	.332	1.000								
V_{11}	.104	.178	-.018	-.613	.260	.039	-.034	.272	.268	-.274	1.000							
V_{12}	.090	**.964**	-.099	-.203	-.158	.010	-.128	-.152	-.134	-.069	.293	1.000						
V_{13}	.413	-.027	-.025	.108	-.238	-.015	-.066	-.051	-.005	.319	-.142	-.042	1.000					
V_{14}	-.041	-.006	-.020	-.087	.615	-.011	-.043	-.057	-.049	-.660	.482	.024	-.208	1.000				
V_{15}	.352	-.153	-.122	-.104	-.188	.215	.154	.193	.153	.364	.131	-.121	.095	-.064	1.000			
V_{16}	-.035	-.218	-.059	.385	-.126	-.125	-.169	.423	.521	.405	-.034	-.178	.175	-.004	-.039	1.000		
V_{17}	-.113	-.020	.049	.581	-.059	-.117	-.070	-.244	-.193	-.011	-.408	-.079	.131	.090	-.274	.205	1.000	
V_{18}	.050	.133	.031	-.292	.161	.124	.036	-.318	-.337	-.352	.023	.090	-.138	-.019	.155	**-.851**	-.111	1.000

This table presents a correlation analysis of variables examined in this study.

There is significant correlation relationship between 1.) V_2 (Efficiency ratio) and V_{12} (Noninterest expenses to earning assets), 2.) V_5 (Loss allowance to loans) and V_{10} (Net operating income to assets), 3.) V_8 (Yield on earning assets) and V_9 (Net interest margin) and 4.) V_{16} (Equity capital to assets) and V_{18} (Core capital (leverage) ratio).

This observation brings us to eliminate four variables from the model to avoid having a biased model. The eliminated variables are 1.) V_5 (Loss allowance to loans), 2.) V_9 (Net interest margin), 3.) V_{12} (Noninterest expenses to earning assets) and 4.) V_{18} (Core capital (leverage) ratio).

Table 5 presents the correlation matrix for the remaining variables. From Table 5, we conclude the absence of multicollinearity for all remaining variables. All correlation coefficient between the remaining independent variables are less than 0.8 in absolute values.

Table 5. Correlation Matrix of the Independent Variables

	V_1	V_2	V_3	V_4	V_6	V_7	V_8	V_{10}	V_{11}	V_{13}	V_{14}	V_{15}	V_{16}	V_{17}
V_1	1.000													
V_2	.126	1.000												
V_3	-.077	-.091	1.000											
V_4	-.201	-.164	-.031	1.000										
V_6	.207	.038	-.019	-.138	1.000									
V_7	.039	-.156	.015	-.073	-.209	1.000								
V_8	-.264	-.272	-.085	-.170	-.207	.253	1.000							
V_{10}	.128	-.082	-.056	-.183	.024	-.052	.276	1.000						
V_{11}	.104	.178	-.018	-.613	.039	-.034	.272	-.274	1.000					
V_{13}	.413	-.027	-.025	.108	-.015	-.066	-.051	.319	-.142	1.000				
V_{14}	-.041	-.006	-.020	-.087	-.011	-.043	-.057	-.660	.482	-.208	1.000			
V_{15}	.352	-.153	-.122	-.104	.215	.154	.193	.364	.131	.095	-.064	1.000		
V_{16}	-.035	-.218	-.059	.385	-.125	-.169	.423	.405	-.034	.175	-.004	-.039	1.000	
V_{17}	-.113	-.020	.049	.581	-.117	-.070	-.244	-.011	-.408	.131	.090	-.274	.205	1.000

This table shows a correlation matrix of the independent variables.

Table 6 presents the logistic regression estimates of the equation:

$$F_t = \alpha_0 + \alpha_1 V_1 + \alpha_2 V_2 + \alpha_3 V_3 + \alpha_4 V_4 + \alpha_5 V_6 + \alpha_6 V_7 + \alpha_7 V_8 + \alpha_8 V_{10} + \alpha_9 V_{11} + \alpha_{10} V_{13} + \alpha_{11} V_{14} + \alpha_{12} V_{15} + \alpha_{13} V_{16} + \alpha_{14} V_{17} + \varepsilon_i$$

Where:

1.) V_1 is the Assets per employee, 2.) V_2 is the Efficiency ratio, 3.) V_3 is the Cash dividends to net income, 4.) V_4 is the Net loans and leases to core deposit, 5.) V_6 is the Net loans and leases to deposits, 6.) V_7 is the Cost of funding assets, 7.) V_8 is the Yield on earning assets, 8.) V_{10} is the Net operating income to assets, 9.) V_{11} is the Noninterest income to earning assets, 10.) V_{13} is the Return on assets, 11.) V_{14} is the Return on equity, 12.) V_{15} is the Retained earnings to average equity, 13.) V_{16} is the Equity capital to assets and 14.) V_{17} is the Growth ratio 1.

We created lagged variables for one year, two years and three years before the year a bank perpetrates fraud. Hence, the structure of our variables is $V_{i,t}$, $V_{i,t-1}$, $V_{i,t-2}$, $V_{i,t-3}$, where i varies from 1 (V_1) to 17 (V_{17}). The results presented in Table 6 show that eleven variables selected by the logistic regression procedure (Forward Stepwise) to be in the model, explain the fraud at 59.1% for Cox and Snell Pseudo R^2 and 71.1% for McFadden Pseudo R^2. Both measures are a good value for a logistic regression performed on a number of observations of 120 (10 banks observed over 12).

Table 6 shows that nine ratios out of eleven variables are significant. These ratios measure performance. We conclude that hypothesis $H1_1$ (banks with low performance ratios are exposed to a greater occurrence of managerial fraud) is verified. The ratio V_1 also measures growth (Growth ratio) and is significant. We conclude that the hypothesis $H2_1$ (banks with high growth ratios are exposed to a greater occurrence of managerial fraud) is verified. The absence of significant Capital ratios allows us to reject hypothesis $H3_1$ (banks with low capital ratios are exposed to an increased frequency of managerial fraud).

Table 6. Logistic Regression Parameter Estimates

	B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound
Intercept	25.468	9.784	6.775	1	0.009*		
$V_{1,t-3}$	0.0000	0.0000	8.069	1	0.005*	1.0000	1.0000
$V_{2,t-2}$	-413.85	162.54	6.482	1	0.011*	0.0000	0.0000
$V_{2,t-3}$	-611.12	242.45	6.353	1	0.012*	0.0000	0.0000
$V_{3,t}$	0.7170	1.084	0.4370	1	0.509	2.0480	0.2450
$V_{3,t-3}$	4.576	2.265	4.083	1	0.043**	97.115	1.147
$V_{4,t}$	14.160	7.693	3.388	1	0.066***	1,411,872	0.3990
$V_{4,t-1}$	-24.031	9.102	6.970	1	0.008*	0.0000	0.0000
$V_{6,t}$	-0.3820	0.4880	0.6150	1	0.433	0.6820	0.2620
$V_{10,t}$	-248.48	96.74	6.597	1	0.010*	0.0000	0.0000
$V_{11,t}$	-804.13	295.04	7.428	1	0.006*	0.0000	0.0000
$V_{14,t-2}$	-97.042	38.227	6.444	1	0.011*	0.0000	0.0000
Cox and Snell Pseudo R^2: 59.1%					McFadden Pseudo R^2 : 71.1%		

*This table shows Logistic Regression Parameter Estimates. Significant at: *1%, **5% and ***10% (***)*

The model for prediction and detection of fraud in the Financial Statements of Tunisian Banks can be written as follow:

$$F_t = -413.85V_{2,t-2} - 611.12V_{2,t-3} + .72V_{3,t} + 4.58V_{3,t-3} + 14.16V_{4,t} - 24.03V_{4,t-1} - .382V_{6,t} - 248.48V_{10,t} - 804.13V_{11,t} - 97.04V_{14,t-2} + 25.47 \quad (3)$$

Table 7 measures how well the model predicts the dependent variable based on the independent variables. The percentage of correct classification of banks as non-fraudulent is 93.4% and for fraudulent banks 82.8%. The Overall Percentage classification rate is 90%, which is a good classification rate.

From this analysis, we conclude that Tunisian banks having low performance or high growth ratios are exposed to commit managerial fraud. However, Tunisian banks having low capital ratios are less exposed to commit managerial fraud. The logistic regression model developed is a good tool for detecting and predicting managerial fraud for Tunisian Banks. This model shows and confirms (McAteer (2009)) findings that managerial fraud is a process that can take up to three years before its occurrence and detection.

Table 7. Classification rate

Observed	**Predicted**		
	0	1	Percent Correct
0	57	4	93.4%
1	5	24	82.8%
Overall Percentage	68.9%	31.1%	90.0%

This table shows classifications rates.

CONCLUSION

Garner (2009) defined Fraud as "A knowing misrepresentation of the truth or concealment of a material fact to induce another to act to his or her detriment." Fraud in financial statements is defined differently in the professional and academic literature. The results of the latest report published by the Association of Certified Fraud Examiners (ACFE) in 2012 are alarming. Indeed, the lighthouse observation of this report is that fraud costs 5% of total annual turnover of the companies affected. Moreover, banks are ranked first among companies as victims of fraud.

This paper presents a model for prediction and detection of fraud for Tunisian banks. The methodology is to examine a battery of financial ratios used by the Federal Deposit Insurance Corporation (FDIC) as indicators of the financial situation of a U.S. bank. We test their predictive power before the occurrence of fraud. The results obtained by performing a logistic regression, show that Tunisian banks having low performance or high growth ratios are exposed to commit managerial fraud while Tunisian banks having low capital ratios are less subject to increased frequency of managerial fraud.

The logistic regression model developed in this paper explains the fraud at a 59.1% rate for Cox and Snell Pseudo R^2 and 71.1% for McFadden Pseudo R^2. Both measures are good values for our logistic regression. The Overall Percentage classification rate is 90%, which is a good classification rate for the model. Many users, such as, the Financial Market Council (the Tunisian equivalent of the SEC), the Government Accountability Office, the auditors, among others can rely on the model developed in this paper and use it as a tool to detect and predict managerial fraud.

This work should be taken with caution. The model developed cannot be universal. All findings are related to the bank sample used as well as the period of study. In fact, during the period 1999 to 2010, Tunisia observed weak governance not only for the government but also for large state owned companies. This may bias our results. However, our model can be validated by using data mining techniques as a tool for detecting financial statement managerial fraud.

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