SCHOOL OF BUSINESS ADMINISTRATION
DEPARTMENT OF ACCOUNTING AND FINANCE
MSc IN APPLIED ACCOUNTING AND AUDITING

Master's Thesis

DETECTING THE PROBABILITY OF FINANCIAL FRAUD DUE TO EARNINGS MANIPULATION IN COMPANIES LISTED AT ATHENS STOCK EXCHANGE MARKET

by

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A thesis submitted in part fulfilment of the requirements for the completion of MSc in Applied Accounting and Auditing

Thessaloniki 2019

CONTENTS

ABSTRACT

One of the main goals for every company is to stay prosperous and maximize its profit. Therefore, their financial statements should reflect a healthy and profitable corporate condition so as to allure investors and funds. This is why many companies try to tamper with their published financial statements in order to present a favorable financial condition. A well-known method of financial fraud is earnings manipulation which includes accounting techniques to falsely present an overly positive corporate view or to hide a deficient economic position. This study focuses on the definition of financial fraud and earnings management, analyzes the most common incentives for financial fraud and recommends protection measures according to recent literature. It also presents famous studies on financial fraud detection that have been developed over the last two decades. One of them is Beneish model that examines the probability of a company to commit financial fraud due to earnings manipulation. This study uses M-Score as indicated by Beneish to detect possible earnings manipulation suspects listed in the General Index of Athens Stock Exchange Market during 2017-2018. According to the findings, 17.5 percent of the sample is likely to conduct earnings manipulation as these companies had an M-Score higher than -2.22. Beneish model offers a probability of financial fraud and can be therefore used as a supplementary test for auditors, fraud examiners or even national regulators such as the Hellenic Accounting and Auditing Standards Oversight Board or the Hellenic Capital Market Commission. The results of this study can contribute to the literature concerning financial fraud in Greece since no relevant recent researches have been published yet.

ΠΕΡΙΛΗΨΗ

Ένας από τους σημαντικότερους στόχους μιας επιχείρησης είναι η συνεχής ευημερία και η μεγιστοποίηση των κερδών της. Αυτό συνεπάγεται ότι οι εταιρείες επιδιώκουν να παρουσιάζουν μια υγιή και επικερδή χρηματοοικονομική θέση ώστε να προσελκύσουν επενδυτές και κεφάλαια. Για αυτό το λόγο πολλές εταιρείες καταφεύγουν στην παραποίηση των δημοσιευμένων χρηματοοικονομικών τους καταστάσεων ώστε να παρουσιάσουν μια ευνοϊκή εικόνα της οικονομικής τους θέσης. Μια γνωστή μέθοδος λογιστικής απάτης από μια εταιρεία είναι η χειραγώγηση κερδών που στηρίζεται στη χρήση λογιστικών τεχνικών για να παρουσιάσει μια ψεύτικη υπεραισιόδοξη οικονομική θέση ή για να κρύψει μια ζημιογόνα οικονομική θέση. Η συγκεκριμένη μελέτη εστιάζει στον ορισμό της λογιστικής απάτης μέσω ψευδών χρηματοοικονομικών καταστάσεων και τη χειραγώγηση κερδών, τα συνηθέστερα κίνητρα που οδηγούν στην απάτη καθώς και τρόπους προστασίας από μια πιθανή απάτη σε επίπεδο επιχείρησης σύμφωνα με την πρόσφατη βιβλιογραφία. Επιπλέον, περιλαμβάνει σύντομη περιγραφή των δημοφιλέστερων μοντέλων ανίχνευσης πιθανότητας λογιστικής απάτης που αναπτύχθηκαν στη διάρκεια των δύο τελευταίων δεκαετιών. Ένα από αυτά αποτελεί το μοντέλο που αναπτύχθηκε από τον Beneish και εξετάζει την πιθανότητα ύπαρξης λογιστικής απάτης σε μια εταιρεία λόγω χειραγώγησης κερδών. Η παρούσα μελέτη χρησιμοποιεί τη βαθμολογία M-Score όπως υποδείχθηκε από τον Beneish για την ανίχνευση πιθανών “χειραγωγών” εταιρειών, εισηγμένων στο Γενικό Δείκτη του Χρηματιστηρίου Αξιών Αθηνών κατά τη διάρκεια 2017-2018. Σύμφωνα με τα αποτελέσματα, το 17.5 τοις εκατό του δείγματος είναι πιθανό να ασκεί χειραγώγηση κερδών καθώς οι συγκεκριμένες εταιρείες παρουσίασαν M-Score υψηλότερο από -2,22. Το μοντέλο του Beneish μπορεί να δείξει αν υπάρχει πιθανότητα ύπαρξης χειραγώγησης κερδών και συνεπώς μπορεί να χρησιμοποιηθεί επικουρικά κατά τον έλεγχο από έναν ορκωτό ελεγκτή, από εποπτικές αρχές αλλά και οργανισμούς που διερευνούν υποθέσεις απάτης. Τα ευρήματα της παρούσας έρευνας δύνανται να συνεισφέρουν στην τρέχουσα βιβλιογραφία αναφορικά με την πιθανότητα ύπαρξης λογιστικής απάτης λόγω χειραγώγησης κερδών στις ελληνικές επιχειρήσεις καθώς δεν έχουν δημοσιευθεί παρόμοιες έρευνες για τα έτη 2017-2018.

CHAPTER 1

INTRODUCTION

1.1 Introductory Comments

Companies have always dealt with fraudulent activity ever since they started running. During recent years many different ways have been invented in order to commit corporate fraud. According to the Report of the Nations on Occupational Fraud issued by the association of Certified Fraud Examiners, 10% of fraud cases found solely in 2018 around the globe refers to financial statement fraud. Financial statement fraud is defined as the act of misinterpreting or misstating the published financial statements in order to deliberately present false information about the company. One of the most notorious techniques of financial fraud is earnings management which constitutes the use of accounting techniques and standards so as to present an overly positive view of a company's financial statements or to hide a seemingly deficient economic position. The execution of earnings manipulation usually involves activities such as recognition of huge fictitious accruals, capitalization of intangible assets, recognition of large sums of expenses during profitable years.

Therefore, there have been many studies in the academic literature (Persons, Green and Choi, Summers and Sweeney, Beneish, Spathis, Kirkos, Cecchini) concerning ways to discover whether a company commits fraudulent activity. These famous researchers have studied and developed scientific models that examine the probability of financial statement fraud. Some studies use linear regression models in order to exact significant results whereas others use neural network and artificial intelligence models.

1.2 Scope and research questions

This study uses Beneish model to examine the possibility of financial statement fraud due to earnings management. Beneish model uses eight variables created by information derived from the financial statements (Balance Sheet and Income Statement) of the companies. These variables are Days Sales in Receivables Index (DSRI), Gross Margin Index (GMI), Asset Quality Index (AQI), Sales Growth Index (SGI), Depreciation Index (DEPI), Sales General and Administrative Expenses Index (SGAI) , Leverage Index (LVGI), Total Accruals to Total Assets (TATA). These eight variables are then multiplied by eight coefficients calculated by Beneish through linear regression which produces M-Score for every company. The M-Score represents earnings manipulation. According to his study, Beneish estimates that any company with M-Score -2.22 or above is likely to be a manipulator whereas any company that scores -2.22 or less is unlikely to conduct earnings manipulation.

Therefore, the purpose of this study is to examine the probability of financial statement fraud due to earnings manipulation in Greece during 2017-2018 using Beneish model. The results of this study can contribute to the literature concerning financial fraud in Greece since no relevant recent researches have been published yet. The sample involves all company stocks that belong to General Index of Athens Exchange Stock Market during 2017-2018.

1.3 Structure

This study begins by defining the notion of financial fraud and earnings management using published literature and information from esteemed organisations. It then proceeds to analyze the motivation and behavioral aspect for conducting financial fraud. There is also plenty of statistical information regarding financial fraud cases around the globe in 2018. The study continues by presenting the Greek Law on financial fraud and recommending protection measures such acts. The literature review ends with a quick summary of the most known studies regarding financial fraud detection that have been published through the years.

The research methodology then follows to describe Beneish model, the used sample, analyze the methodology and present the results.

Finally, the study wraps up with the conclusions produced by the model and some proposals for future studies.

CHAPTER 2
LITERATURE REVIEW

2.1 Definition of Financial Fraud and Earnings Management

The subject of fraud has always been a huge topic among the financial institutions and academic studies since they started to appear. There have been many definitions of "financial fraud": According to Koya et al., (2014), financial fraud can be defined as an act of misinterpretation or misstatement of the published financial reports by financial market participants in order to deliberately or involuntarily provide false or manipulated information about the company. This misleading financial information can violate any accounting rule, regulatory rule or any type of law. The Association of Certified Fraud Examiners, defines financial statement fraud as the act of overstating the revenue, assets, or profits and understating the expenses, liabilities or losses. This type of fraud includes timing differences between accounting dates, fictitious or understated revenues, concealed or overstated liabilities and expenses, improper asset valuations and improper disclosures. According to The 2018 Report of the Nations by the aforementioned institution, 8% of fraud cases in companies in Western Europe (including Greece) were financial fraud which constitutes the third most popular type of fraud in the area. Specifically, in 2018 there were 22 fraud cases in Greek companies out of 130 cases in Western Europe. The same study reports that a financial statement fraud usually lasts for 24 months.

One of the most notorious means of financial fraud in recent years, is earnings management which constitutes the use of accounting techniques in order to falsely present an overly positive view of a company's financial statements or to hide a seemingly deficient economic position. Earnings management usually takes advantage of the vague accounting rules or misinterpretation of the (GAAP) Generally Accepted Accounting Principles so as to present a retouched image of an organisation's financial position. Managers may use legal or illegal techniques to achieve specific earnings goals (Tabassum et al., 2015). Some of these techniques include:

- “cookie from the jar”

This action takes advantage of the accrual-based accounting in periods of high profits. When a company manages strong revenue in a fiscal year, managers make a reserve of accrued expenses in order to make sure that they keep a balanced corporate financial position in the long term. Therefore, during high-earnings periods, the organisation establishes additional expense accruals so as to smoothen the current earnings report to make up for future low-earnings periods by pulling a “cookie from the jar”. This technique is mostly used by companies who are heavily income-targeted driven.

- Capitalization of intangible assets

Many companies choose to capitalize a large sum of development or research and development costs on their balance sheet in order to reduce their expenses due to the subjective nature of such costs. According to IAS 38, these costs can be amortized under certain circumstances; thus appear in the income statement and subsequently reduce the profits.

- “Big bath”

This technique is prefered during low income periods when managers establish a huge one-time expense in order to further worsen a company’s financial report and subsequently present an artificial spectacular rise in profits in the next fiscal year. Executives may opt for the aforementioned action so that they get a reward from the management for achieving profit targets.

- Merger and acquisitions

Earnings management can play a huge role in a pending merger or acquisition activity. Managers may establish a huge artificial expense linked to the purchase of a company. Thus, the acquirer can take advantage of that accrued expense and on the other hand the seller can establish a large goodwill on their balance sheet. However, Managers may also tamper with the income statement by showing weaker financial data of a company in order to avoid an undesired merger.

2.2 Motivation for Financial Fraud

But why do managers engage in such acts in the first place? What is the motivation behind earnings manipulation and why do firms feel the need to tamper with the financial statements? The Association of Certified Fraud Examiners has compiled a series of suspicious behaviors also known as “red flags”, which according to them creates the profile of a potential fraudster since 85% of their cases displayed at least one such “red flag”. On that account, the 6 behavioral “red flags” of fraudulent activity include: (i) living beyond means, (ii) history of financial difficulties, (iii) unusually close association with vendor/customer, (iv) control issues, unwillingness to share duties, (v) personal/family problems, (vi) “wheeler-dealer” attitude.

Recent literature suggests there are two factors acting as a driving force for financial misstatement: human behavior and capital market motivations. According to Amiram et al., (2018) managers who may engage in any type of misconduct in their personal or professional life are more likely to participate in an earnings mismanagement. Besides, social and geographical background of corporate executives as well as the local social framework of a company may encourage financial misconduct. The authors also reckon that managers might falsify corporate earnings statements in order to meet stressful goals linked to rewards assigned by the higher management. According to the Report to the Nations (Association of Certified Fraud Examiners, 2018), there is a correlation between the perpetrator’s level of authority and the importance of the fraud. 44% of global fraud cases in 2018 involved an employee, 34% a manager and 19% the owner or a higher executive while the rest 3% includes other staff. However, when an owner/executive committed fraud they scored a median loss of $850,000 for the company whereas an employee only $50,000. Moreover, the most common perpetrator’s tenure seems to be 1-5 years in the company followed by veteran employees who have been employed for over a decade in the same company.

Capital market motivations (Amiram et al., 2018) are mostly associated with the financial position of the company towards external stakeholders. A common motivation consists of the desire to raise the company’s stock price in order to become more appealing to potential investors. Managers delve into earnings manipulation so as to present a healthier and more profitable financial position of the company in order to boost its popularity in the stock exchange market. Thus, executives profit from different kind of rewards from the management associated with the profitable financial course of the company.

Another capital market motivation linked to the company's will to attempt financial fraud is the need for a loan or financing from a credit organisation (Amiram et al., 2018). Firms tend to manipulate their financial statements, especially by understating their liabilities or overpricing their assets, in order to ameliorate their financial position and as a result increase their chances on getting external capital with low interest rate and favorable conditions. Credit institutions require that their customers dispose healthy financial ratios and profitable perspectives so that they can pay off their credit plus any interest rate on time.

2.3 Financial Fraud Cases Around the World in 2018

The Association of Certified Fraud Examiners issued a report (Report to the Nations, 2018) providing evidence, information and statistics on financial fraud cases occurred in 2018 in companies around the globe. According to this report, 2,690 cases of occupational fraud were discovered in a single year, 10% of which refers to financial statement fraud from 125 countries in 23 industry categories. These fraud cases make up for over $7 billion in total losses and $130,000 median loss per case. The median duration of a fraud scheme is 16 months while corruption was the most common scheme of fraud in every global region. However, according to the recent report, financial statement fraud schemes are the least common and most costly fraudulent activities which may cost a median loss of $800,000 for a company.

Table 1: Fraud cases per region

Region	***Number of cases***	***Percentage of global cases***	***Median loss***
United States	1,000	48%	$108,000
Sub-Saharan Africa	267	13%	$90,000
Asia-Pacific	220	11%	$236,000
Western Europe	130	6%	$200,000
Latin America and the Caribbean	110	5%	$193,000
Middle East and North Africa	101	5%	$200,000
Southern Asia	96	5%	$100,000
Eastern Europe and Western/Central Asia	86	4%	$150,000
Canada	82	4%	$200,000

Table 1 showcases information about reported cases of fraud in different regions globally. More specifically, it seems that the most cases of financial misconduct were discovered in the United States with a median loss of $108,000 per case. Even though in Asia-Pacific region only 220 fraud cases were reported, they caused a median loss of $236,000 which is more than any other cases in the world. On the other hand, the region with the lowest median loss of $90,000 per case is Sub-Saharan Africa with 267 total reported cases. As far as the Western Europe is concerned where Greece is also included, 130 fraud cases were discovered which makes up for 6% of total cases in the world, according to the study, and caused $200,000 median loss (per case), almost twice as much as the ones in the United States. The least number of cases (82) were located in

Canada which constitutes about 4% of the total sample and cost a median loss of roughly $200,000.

As expected, it is a matter of time before a fraudulent scheme is discovered. The same applies to financial fraud cases which sooner or later are uncovered by different detection methods. The Association of Certified Fraud Examiners finds that the most popular means of initial fraud detection is tip (40% of cases) by employees, customers, vendors or even competitors. Internal audit and management review follow suit as the next most usual means of detection. Among the least popular techniques of corporate fraud detection are notifications by law enforcement, IT controls and confessions by the suspect. These findings show that fraudulent activity can be mostly detected by internal factors which tend to provide more information about the financial activity of the company rather than external elements that are not very engaged in a firm's operations. The report also indicates that there is an association between the detection techniques and the severity of the fraud. For instance, tip detection takes a median of 18 months to discover fraud which may lead to a loss of $126,000 whereas external audit may take 23 months to uncover a fraud with a median loss of $250,000.

The most often types of victim-organizations by fraud are private companies (42%) followed by public companies (29%) globally. What is remarkable, is the fact that small businesses, with less than 100 employes, present more fraud risk than the bigger ones. 28% of the global fraud cases were discovered in a company with less than 100 employees scoring a median loss of $200,000. On the other hand, large businesses with over 10,000 employees make up for 24% of the overall fraud cases with a median loss of $132,000. Thus, according to the Nations Report, small businesses lose almost twice as much per scheme to fraud. As expected, the report findings show that the majority of frauds in small businesses are caused by lack of internal controls (42%) whereas companies that occupy more than 100 employees detect fraudulent activity mostly by tip (44%) rather than internal controls (25%). Another interesting finding, is the fact that financial statement fraud specifically is more frequent in small businesses(16%) rather than in large ones (7%). The most popular fraud technique in both small (32%) and large firms (43%) is corruption.

2.4 Greek Law on Financial Fraud

It seems that companies are exposed to different perils regarding financial fraud causing huge losses. This is where the importance of law existence is needed to deter potential perpetrators and protect firms from fraudulent activities. As far as the Greek law on fraud is concerned, Anagnostopoulos and Tolakis, (2018) state that the main regulatory provision and legislation relevant to corporate fraud is the Criminal Code. More specifically, Article 386 of the Criminal Code defines fraud as "enriching oneself or a third party by knowingly representing untrue facts as true or by illegally concealing or suppressing true facts and persuading another to act or omit to act, so as to cause financial damage." The Greek law also recognizes accounting fraud according to Law 2190/1920 "as the act of drawing up or approving inaccurate or false balance sheets or making false declarations to the public on the status of the company in order to achieve, for example, the subscription of new shares." These aforementioned acts are worthy of punishment when committed with intent regardless of whether any damage was incurred or not. Besides, according to the article 390 of the Criminal Code, mismanagement of company funds is defined as the act when "the perpetrator intentionally incurs losses to another's wealth (usually a legal entity) administrated by him."

Once an act has been prosecuted as corporate fraud the perpetrator is then submitted to civil/administrative or criminal proceedings and/or penalties depending on the importance of the case. Potential administrative sanctions imposed by the Greek regulatory authority on either individuals or corporate bodies may include

- Dismissal (if the perpetrator is a civil servant)
- Occupational ban
- Licence revocation (if it is needed to conduct business)
- Permanent or temporary ban from public tenders or state funding

Criminal penalties involve:

- Prison sentence of three months to five years
- Prison sentence of up to ten years if the perpetrator commits fraud on a regular basis having caused an aggregated damage or a total enrichment that exceeds 30,000€ or only if the aggregated damage or total enrichment exceeds 120,000€.

- Prison sentence of up to 15 years if fraud is committed against the state or other public entity and the damage caused exceeds 120,000€ (Article 386, paragraph 2, Criminal Code).
- Confiscation of the proceeds of the crime (Article 76, paragraph 1, Criminal Code).
- Publication of the court decision (Article 68, Criminal Code).
- Deprivation of civil rights (Articles 59 to 66, Criminal Code).

Even though there is quite a strict punishment for fraud criminals, the findings in the Report to the Nations show that, there has been a steady decline in the frequency of the victim organization referring to law enforcement in the past decade (2208-2018) globally. More specifically, 69% of the cases found in 2008 were referred to law enforcement whereas in 2018, only 58% of the fraud schemes ended up being handed over for prosecution. The study goes on to show that the perpetrators involved in cases referred to law enforcement, ended in a plea agreement (53%) or a conviction at trial (20%) whereas 18% was declined to be prosecuted by the law enforcement. Only 1% of defendants was acquitted. The main reasons why organizations decided not to refer cases to law enforcement are fear of bad publicity (38%) and internal discipline that was claimed to be sufficient (33%). The potential high cost of legal prosecution (24%) follows as the next most popular reason while private settlement takes up 21% of the cases.

2.5 Protection Measures Against Financial Fraud

So, what do companies do to prevent fraudulent activity? The International Ethics Standard Board for Accountants has created a code of ethics which presents a number of fundamental principles that a professional accountant should possess during his work. According to the most recent Code of Ethics as offered by the International Ethics Standard Board for Accountants, there are five fundamental principles of ethics for professional accountants: integrity, objectivity, professional competence and due care, confidentiality, professional behavior. Therefore, every accountant should comply with the code of ethics and each company should make sure that every employee is aware of that code using training and teaching techniques on a regular basis. This way, the employees would be deterred from conducting any form of fraudulent activity since the code of ethics does not tolerate any according actions.

The report to the Nations shows that in 2018, the most popular anti-fraud controls include code of conduct, external audit of financial statements and of internal controls over financial reporting, internal audit department, management review, independent audit committee, employee support programs, anti-fraud policy, fraud training for managers and employees. Therefore, these findings seem to stress the importance of the employees' culture and behavior regarding fraudulent activity and the audit of financial statements. According to The Report to the Nations, as far as the internal audit weaknesses is concerned, the lack of internal controls, override of existing controls and lack of management review seem to be the most popular activities that contribute to the appearance of fraud.

2.6 Studies on Financial Fraud Detection Through Years

Persons is one of the first researchers to publish a study on financial fraud detection using publicly available financial information. In his study (Persons, 1995) Persons suggests that financial leverage, capital turnover, asset composition and firm size are the key factors connected to fraudulent financial reporting. He uses logistic linear regression models to extract results for fraud and non-fraud firms using data from the previous year and the fraud year. He uses data from 200 firms (100 fraud and 100 non-fraud) to extract findings for his research.

Green and Choi, (1997), developed a model based on neural network in order to conclude whether a company has engaged in financial misconduct. They used endogenous financial information including 5 ratio and 4 accounting variables in their model. The sample consists of 95 firms (46 fraud and 49 non-fraud). They suggest that their model is mostly useful for auditors prior their field work so as to track the falsified financial statements and organize their audit plan accordingly.

Summers and Sweeney, (1998) studied the connection of insider trading with financial fraud. They used 6 financial factors in logistic regression using a total sample of

102 firms (52 fraud and 52 non fraud). According to their findings, insiders in fraudulent firms seem to reduce their net position in the firm's stock by selling a large number of their stocks. Moreover, companies that indulge in financial misconduct tend to have more inventory relative to sales, higher growth rate and higher return on assets as opposed to non-fraudulent firms.

Beneish, (1999), uses 8 financial variables collected from the publicly available financial statements of the traded companies. He then uses regression to check whether these ratios are representative for earnings manipulation. His sample consists of 2406 firms (74 fraud and 2332 non-fraud) and their annual reports of 2 years (current and one prior year). He concludes that there is an association between earnings management and financial statements. More on his methodology and data processing are described on following chapters.

Spathis et al. (2002) in their research seem to confirm Beneish's theory that published financial statements are connected to earnings management. In order to prove the aforementioned estimation, they use 10 financial variables in the form of ratios and then run a regression model to further assure their theory.They also use multicriteria decision aid (MCDA) and the application of the UTADIS classification method to extract results. Their data include 76 firms (38 fraud and 38 non-fraud), all being traded in Greek stock market.

In their research, (Kirkos et al.,2007) use Data Mining techniques to detect fraudulent activity in companies. More specifically, they use Decision Trees, Neural Networks and Bayesian Belief Networks to identify financial fraud. The input data is composed by 10 financial ratios all of which are available from published financial statements. The sample consists of 76 firms (38 fraud and 38 non-fraud), all of which are traded in Greek stock market. According to their findings, Bayesian Belief Networks (90.3% accuracy) seems to be the most effective method regarding the performance aspect of classifying fraud and non-fraud companies, followed by Neural Networks (80%).

(Cecchini et al., 2010) use Support Vector Machines and a financial kernel method to identify fraudulent companies. In their study, they use 23 attributes to make financial ratios and insert them as an input for their model. Their data consist of 3324 firms (137 fraud and 3187 non-fraud). According to their findings, their model managed to identify correctly 80% of the fraudulent companies of their sample.

From the aforementioned literature review on different methods of detecting financial fraud, it can be deduced that there are two main research methods used on finding out whether a company is fraudulent. Some researchers (Persons, 1995; Summers and Sweeney, 1998; Beneish, 1999; Spathis et al, 2002) use logistic regression to associate published information from financial statements and corporate misconduct whereas others use more modern methods such as neural networks, decision trees and financial kernels (Green and Choi, 1997; Kirkos et al., 2007; Cecchini et al., 2010). It is interesting that more recent studies, prefer to use neural networks and financial kernels models to extract information on financial fraud. Besides, most researchers prefer to extract data from the published financial statements of each company rather than rely on internally-produced information (internal audit, employees, auditors, investors etc.).

As far as the data set is concerned, most studies depend on over 100 firm data to make their model more efficient and extract reliable conclusions on the detection of financial fraud. More specifically, (Spathis et al., 2002) and (Kirkos et al, 2007) use data from only 76 firms since their sample consists of companies listed in the Greek Stock exchange market. All other studies have chosen a larger sample since there is more data available for other countries (e.g. US market). Moreover, according to these prior studies, only two of them (Beneish, 1999) and (Cecchini et al., 2010) use different number of fraud and non-fraud companies data. They chose not to match the number of companies where there was found fraudulent activity with the ones that had no financial misconduct. There seems to be a different approach regarding data match among the researchers with no effect on the final efficiency of each model whatsoever.

Table 2: Categorization of prior studies on detection of financial fraud

Study	**Year of publishment**	**Annual Statement-based feature set**	**Classification method(s)**	**Data Set**
Persons	1995	10 financial ratios/variables from previous year	Logistic regression	200 firm-years; 100 fraud, 100 non- fraud
Green and Choi	1997	5 ratio and 3 accounting variables	Neural network	95 firms; 46 fraud,

				49 non-fraud
Summers and Sweeney	1998	6 financial variables	Logistic regression	102 firms; 52 fraud, 52 non-fraud
Beneish	1999	8 financial variables	Regression	2406 firms; 74 fraud; 2332 non-fraud
Spathis et al	2002	10 financial variables	Logistic regression, UTADIS	76 firms; 38 fraud; 38 non-fraud
Kirkos et al.	2007	10 financial variables	Decision Trees, Neural Networks, Bayesian Belief Networks	76 firms; 38 fraud; 38 non-fraud
Cecchini et al.	2010	23 attributes used to generate financial ratios	SVM(Support Vector Machines), financial kernel	3324 firms; 137 fraud; 3187 non-fraud

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Beneish Model

This research is based upon the Beneish model which consists of 8 variables in order to examine the probability of financial statement fraud related to earnings manipulation. More specifically, Beneish uses 8 financial ratios created by information derived from the financial statements (Balance Sheet and Income Statement) of the corporations used in the sample. According to his findings, these variables represent a company's attempt to commit a fraudulent act.

Table 3: Presentation of variables used in Beneish model

Variable Name	**Meaning**
Days Sales in Receivables Index (DSRI)	Examines the ratio between days sales and receivables. Large increase of this variable suggests a higher likelihood of earnings manipulation.
Gross Margin Index (GMI)	Compares the gross margin in previous year with the gross margin in current year. The higher the index the higher the probability of earnings manipulation.
Asset Quality Index (AQI)	Showcases the ratio of non-current assets excluding Property Plant and Equipment (PPE) to total assets between the year t and t-1. There is a positive relation between this index and possible fraudulent activity related to earnings manipulation.
Sales Growth Index (SGI)	Calculates the ratio of sales in current year to sales in previous year. The higher the ratio the higher the likelihood of earnings management due to the high

	expectations regarding the growth rate of a company.
Depreciation Index (DEPI)	Shows the ratio of the rate of depreciation in previous year to the corresponding rate in current year. There seems to be a positive relation between this variable and the probability of manipulation.
Sales General and Administrative Expenses Index (SGAI)	Demonstrates the ratio of Sales General and Administrative Expenses to sales in year t in relation to the corresponding ratio in the previous year. High ratio numbers may signify a higher probability of manipulation.
Leverage Index (LVGI)	Calculates the ratio of total debt to total assets in year t relative to the corresponding ratio in year t-1.
Total Accruals to Total Assets (TATA)	Examines the change in working capital cashless accounts less depreciation to total assets in the current year. Large increases of this ratio may be linked to higher manipulation probability.

Calculation of the 8 variables:

$$DSRI = \frac{\text{Receivables}_t / Sales_t}{\text{Receivables}_{t-1} / Sales_{t-1}}$$

$$GMI = \left(\frac{\text{Sales}_{t-1}\text{-Costs of Goods Sold}_{t-1}}{\text{Sales}_{t-1}} \right) / \left(\frac{\text{Sales}_t\text{-Costs of Goods Sold}_t}{\text{Sales}_t} \right)$$

$$AQI = \left(1 - \frac{\text{Current Assets}_t\text{+Property Plant Equipment}_t}{\text{Total Assets}_t} \right) / \left(1 - \frac{\text{Current Assets}_{t-1}\text{+Property Plant Equipment}_{t-1}}{\text{Total Assets}_{t-1}} \right)$$

$$\text{SGI}=\frac{\text{Sales}_t}{\text{Sales}_{t-1}}$$

$$\text{DEPI}=\left(\frac{\text{Depreciation}_{t-1}}{\text{Depreciation}_{t-1}+\text{Property Plant Equipment}_{t-1}}\right)/\left(\frac{\text{Depreciation}_t}{\text{Depreciation}_t+\text{Property Plant Equipment}_t}\right)$$

$$SGAI=\left(\frac{\text{Selling General Administrative Expense}_t}{\text{Sales}_t}\right)/\left(\frac{\text{Selling General Administrative Expense}_{t-1}}{\text{Sales}_{t-1}}\right)$$

$$\text{LVI}=\left(\frac{\text{Long Term Debt}_t+\text{Current Liabilities}_t}{\text{Total Assets}_t}\right)/\left(\frac{\text{Long Term Debt}_{t-1}+\text{Current Liabilities}_{t-1}}{\text{Total Assets}_{t-1}}\right)$$

$$\text{TATA}= [\text{Current Assets}_t\text{-Cash}_t\text{-Current Liabilities}_t\text{-Current Maturities of LTD}_t\text{-Income Tax Payable}_t - \\ - \text{Depreciation and Amortization}_t] / \text{Total Assets}_t$$

These eight variables are then multiplied by eight coefficients calculated by Beneish. Therefore the M-score model created is shown below:

$$\text{M-Score} = -4.84 + 0.92 \times \text{DSRI} + 0.528 \times \text{GMI} + 0.404 \times \text{AQI} + 0.892 \times \text{SGI} + 0.115 \times \\ \times \text{ DEPI} -0.172 \times \text{SGAI} + 4.679 \times \text{TATA} - 0.327 \times \text{LVGI}$$

According to his study, Beneish estimates that any company with M-Score -2.22 or above is likely to be a manipulator whereas any company that scores -2.22 or less is unlikely to conduct earnings manipulation.

3.2 Sample

In this study, the sample consists of some of the companies listed in the General Index of Athens Exchange Stock Market on August 31st 2019 using data from their published financial statements for 2017 and 2018. The General Index is made up of 60 companies, the most out of any other Index. The companies that are listed in the General Index were chosen due to the fact that they outnumber other Indexes and they belong to different commercial branches. However, in order for the model to be accurate, the companies related to financial services are not taken into consideration since Beneish did not include them in his research. Therefore, 5 banks and 3 other financial services companies are deducted from the sample.

Besides, four other companies were excluded from the sample since some of the variables required for the M-Score were not applicable. More specifically, two of them presented zero revenue and/or cost of sales in either 2017 or 2018 or both years. This issue regards companies in consulting or construction sector and thus the cost of sales can be nonexistent. As a result, DSRI, GMI and SGAI variables could not be calculated for none of them. The third company presented zero depreciation regarding tangible assets and a certain amount of depreciation regarding only intangible assets in 2018. Besides, according to the balance sheet by ICAP database, the company had no tangible assets in 2018. Thus, the variable DEPI cannot be calculated and as a result no M-Score can be given for the specific company. The fourth company left out from the sample, includes a disproportionate difference between the assets in 2017 and 2018. Consequently, the AQI variable is immensely large and therefore it is considered as an outlier for the current model. Finally, eight companies were omitted from the sample since they were found to be outliers for at least one of the following variables.

To sum up, the total sample is ultimately made up of 40 publicly listed companies.Table 4 demonstrates the stock market company symbol used in Athens Stock Exchange Market and the company name included in the sample.

Table 4: Companies included in the sample

Number	Stock Market Company Symbol	Company Name
1	**ΑΒΑΞ**	JP AVAX
2	**ΑΡΑΙΓ**	Aegean Airlines
3	**ΔΕΗ**	Public Power Corporation SA-Hellas
4	**ΕΚΤΕΡ**	Ekter SA
5	**ΕΛΠΕ**	Hellenic Petroleum
6	**ΕΛΤΟΝ**	Elton
7	**ΕΥΑΠΣ**	Thessaloniki Water Supply & Sewerage Company
8	**ΕΥΔΑΠ**	Athens Water Supply & Sewerage Company
9	**ΙΑΣΩ**	Iaso General, Maternity and Gynecological Clinic
10	**ΙΑΤΡ**	Athens Medical Group
11	**ΙΚΤΙΝ**	Iktinos Hellas SA
12	**ΙΝΚΑΤ**	Intrakat
13	**ΙΝΤΕΡΚΟ**	Intercontinental
14	**ΙΝΤΚΑ**	Intracom Holdings
15	**ΚΑΡΤΖ**	Karatzis SA
16	**ΚΕΚΡ**	Kekrops SA
17	**ΚΛΜ**	I. Kloykkinas I. Lappas
18	**ΚΡΙ**	Kri Kri

19	**ΛΑΜΔΑ**	Lamda Development SA
20	**ΛΑΜΨΑ**	Lampsa Hellenic Hotels SA
21	**ΜΛΣ**	MLS Innovations Inc,
22	**ΜΠΕΛΑ**	Jumbo SA
23	**ΜΥΤΙΛ**	Mytilineos
24	**ΝΗΡ**	Nireus Aquaculture
25	**ΟΛΘ**	Thessaloniki Port Authority SA
26	**ΟΛΠ**	Piraeus Port Authority SA
27	**ΟΛΥΜΠ**	Technical Olympic
28	**ΟΤΕ**	Hellenic Telecommunications Organisation
29	**ΟΤΟΕΛ**	Autohellas
30	**ΠΑΠ**	Papoutsanis SA
31	**ΠΕΤΡΟ**	Petros Petropoulos SA
32	**ΠΛΑΙΣ**	Plaisio
33	**ΠΛΑΚΡ**	Plastika Kritis SA
34	**ΠΡΟΦ**	Profile Software
35	**ΣΑΡ**	Sarantis SA
36	**ΤΕΝΕΡΓ**	Terna Energy
37	**ΦΛΕΞΟ**	Flexopack SA
38	**ΦΡΛΚ**	Fourlis
39	**TITC**	Titan Cement

40	**EEE**	Coca-Cola 3E

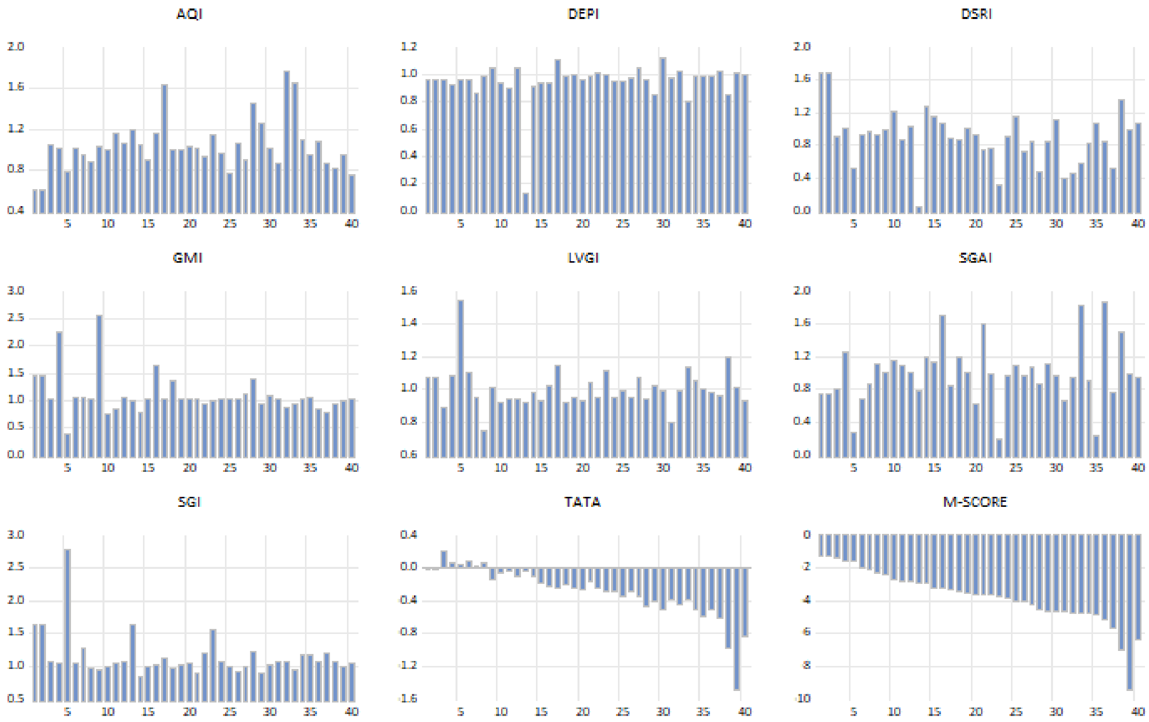
3.3 Methodology

For all the aforementioned companies, the 8 variables mentioned in Beneish model are calculated in order to decide whether there is a possibility of earnings manipulation. The necessary information for the formation of the 8 variables per company was collected from the Financial Statements of each company via ICAP Database or the website of the corresponding entreprise. In this study, data from 2017 and 2018 financial statements of the 40 companies were used for the model. The variables of Beneish model: DSRI, GMI, AQI, SGI, DEPI, SGAI, LVGI, TATA require information from the balance sheet and income statement of each company for the economic years 2017 and 2018. The formulas described above for every single variable were used to calculate the ratios. After estimating the variables, the M-Score for each company used in the sample was calculated.

3.4 Results

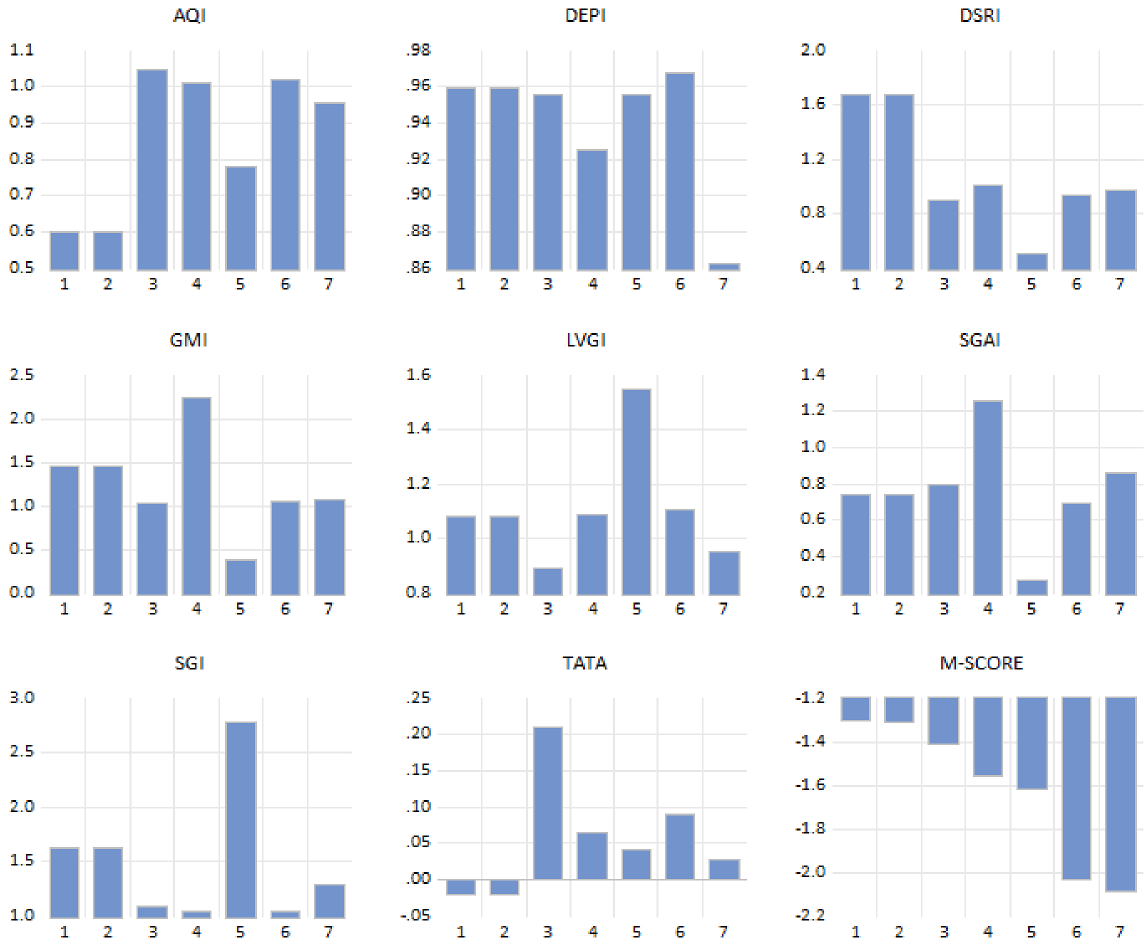
After calculating the M-Score for every company included in the sample, i categorized the companies into two groups according to the possibility of conducting earnings management: Manipulators and Non-Manipulators. According to Beneish's model, if the M-Score for a company is higher than -2.22 then it is more likely to use earnings manipulation whereas if a company scores less than -2.22 it is less likely to use earnings management techniques. Therefore, the companies with M-Score higher than -2.22 are described as Manipulators while companies that scored less than -2.22 are characterized as Non-Manipulators. After taking all the aforementioned information into consideration, it was found that 33 (out of 40) companies had a M-Score value lower than -2.22 and thus are categorized as non-manipulators. In the meantime, 7 companies presented M-Score higher than -2.22 and thus are categorized as manipulators. In other words, 82.5% of the sample is considered rather unlikely to conduct earnings manipulation whereas 17.5% of the companies listed in the General Index of Athens Stock Exchange Market is likely to manipulate its earnings. Below the descriptive statistics for manipulators, non-manipulators and the total sample are presented.

The values for each variable are presented in Graph 1 in independent charts. DSRI, GMI, AQI, SGI, DEPI, SGAI and LVGI variables seem to only have positive values in all companies. Most companies had a negative TATA but a small amount seems to have mildly positive value of TATA. On the other hand, M-Score for all companies included in the sample, non-manipulators and manipulators, possess a negative M-Score.



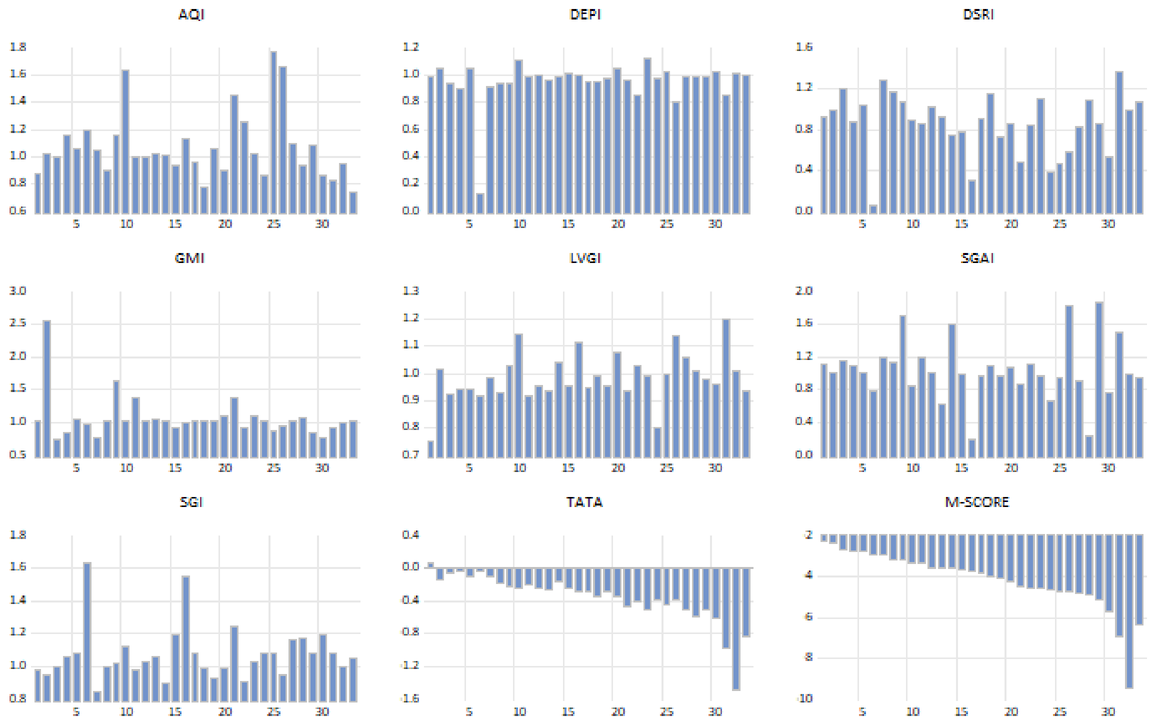
Graph 1: Values of eight variables and M-Score of the sample

The values of the variables of manipulators seem to follow the pattern of the total sample accordingly. More specifically, seven of the variables present only positive values, one variable positive and mildly negative values. The M-Score for manipulators is negative for all companies.



Graph 2: Values of eight variables and M-Score of companies conducting manipulation

The values of the variables regarding non-manipulators present a slight difference than the total sample. Almost all variables except for M-Score have only positive values. One company has positive TATA while all others non-manipulators have negative TATA value. M-Score for all non-manipulators is negative as expected since according to Beneish model, all companies with M-Score lower than -2.22 are rather unlikely to be manipulators and therefore are characterized as non-manipulators.



Graph 3: Values of eight variables and M-Score of non-manipulators

According to Table 5, the mean M-Score for non-manipulators is -4.161 in contrast to -1.619 for manipulators. The standard deviation of manipulators' M-Score is 0.325 in contrast to 1.445 for the non-manipulators which highlights the fact that the M-Score values for non-manipulators are more scattered among the mean (-4.161) value.

The descriptive statistics for the total sample seem to follow Non-Manipulators' values. The mean total is -3.716 compared to -4.1611 for non-manipulators. The standard deviation for total sample is -1.639 and for non-manipulators 1.445. The median regarding the total sample follows a similar pattern.

Table 5: M-Score descriptive statistics

M-SCORE			
	Manipulators	Non-Manipulators	Total
Mean	-1,619	-4,161	-3,716
Median	-1,559	-3,798	-3,619
Maximum	-1,306	-2,273	-1,306
Minimum	-2,091	-9,440	-9,440
Std. Dev.	0,325	1,445	1,639
Skewness	-0,557	-1,653	-1,066
Kurtosis	1,733	6,741	5,188
Sum	-11,331	-137,299	-148,630
Sum Sq. Dev.	0,634	66,808	104,756
Observations	7	33	40

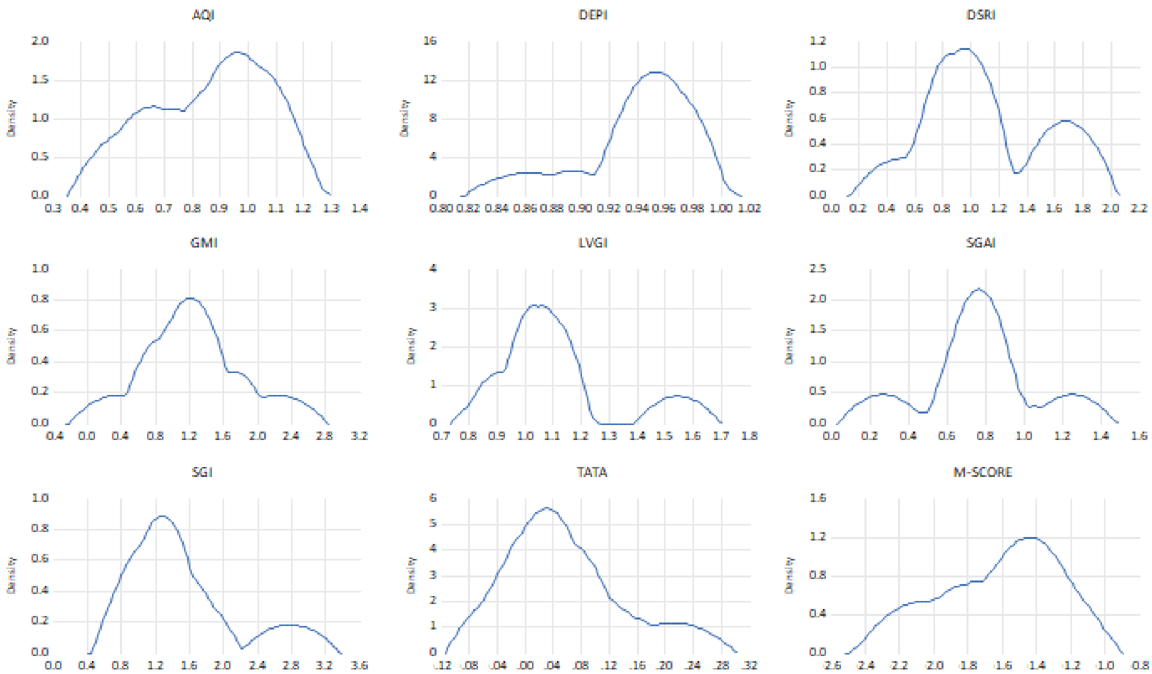
Below is presented the descriptive statistics for each variable for each group separately: manipulators and non-manipulators. The highest mean out of the eight variables regarding manipulators is observed in Sales Growth Index (SGI) which signifies that companies who are likely to commit earnings manipulation, prefer to present higher Sales in relation to sales between two successive years in order to tamper with the income statement. The second highest mean out of the eight variables belongs to Gross Margin Index (GMI) which showcases the sales to the cost of goods sold in relation to the sales to the cost of goods sold value for two consecutive economic years. The mean of LVGI regarding manipulators is the third highest which shows the leverage index between two consecutive economic years. This finding further supports the accuracy of the model since manipulators are more likely to tamper with the sales growth indexes as a form of earnings manipulation in order to ameliorate the financial profile of the company. Besides,the highest maximum value of a manipulator's variable belongs to Sales Growth Index (SGAI). The lowest standard deviation among the eight variables belongs to DEPI index whereas the highest belongs to SGI.

Table 6: Variables descriptive statistics for manipulators

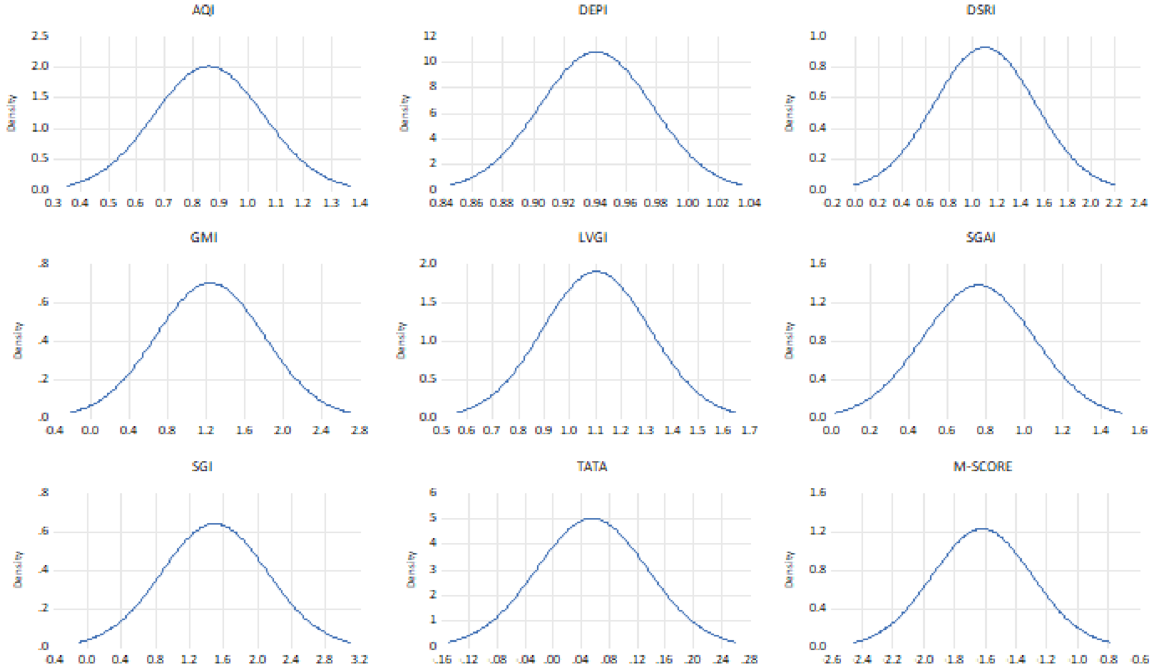
	DSRI	*GMI*	*AQI*	*SGI*	*DEPI*	*SGAI*	*LVGI*	*TATA*
Manipulators								
Mean	*1,097*	*1,239*	*0,858*	*1,498*	*0,941*	*0,766*	*1,104*	*0,055*
Median	*0,967*	*1,065*	*0,954*	*1,285*	*0,955*	*0,743*	*1,079*	*0,042*
Maximum	*1,677*	*2,239*	*1,047*	*2,783*	*0,967*	*1,253*	*1,545*	*0,210*
Minimum	*0,510*	*0,373*	*0,598*	*1,039*	*0,862*	*0,268*	*0,888*	*-0,022*
Std. Dev.	*0,429*	*0,570*	*0,198*	*0,623*	*0,037*	*0,289*	*0,210*	*0,080*
Skewness	*0,396*	*0,340*	*-0,470*	*1,381*	*-1,572*	*-0,047*	*1,388*	*0,989*
Kurtosis	*1,989*	*2,896*	*1,484*	*3,687*	*3,965*	*3,266*	*4,005*	*3,103*
Sum	*7,680*	*8,675*	*6,008*	*10,486*	*6,584*	*5,359*	*7,730*	*0,388*
Sum Sq. Dev.	*1,106*	*1,947*	*0,236*	*2,326*	*0,008*	*0,503*	*0,266*	*0,038*
Observations	*7*	*7*	*7*	*7*	*7*	*7*	*7*	*7*

The highest kurtosis value among manipulators belongs to LVGI variable (4,005) followed by DEPI (3,965). Every variable with kurtosis value greater than 3 is considered as leptokurtic which associates with Graph 5 that shows the Theoretical Distribution for every variable. Leptokurtic distribution is longer and tails are fatter as depicted in Graph 4 for LVGI, DEPI, SGI and SGAI . Peak is high and sharp which means that data are heavy-tailed or profusion of outliers. On the other hand, DSRI and AQI showcase kurtosis value less than 3 which gives the distribution a shorter shape and thin tales. This means that data are light-tailed or lack of outliers. Variables such as TATA and GMI present a value of kurtosis around 3 (3.103 and 2.896 respectively). These variables demonstrate a mesokurtic distribution which means that the extreme values of the distribution are similar to that of a normal distribution characteristic.

Skewness as an element of descriptive statistics shows the degree of distortion from the normal distribution. It measures the lack of of symmetry in data distribution as shown in the graphs below. According to table 6, all variables except for SGI, LVGI and TATA demonstrate positive skewness which means that the tail on the right side of the distribution is longer or fatter. This shape can be further seen in graph 4 which shows the kernel density distribution for manipulators. On the other hand, variables that present negative skewness like DEPI means that the tail of the left side of the distribution is longer or fatter than the tail on the right side. DSRI, GMI, AQI and SGAI distributions are moderately skewed (skewness value between 0.5 and 0.5).



Graph 4: Kernel Density Distribution for manipulators



Graph 5: Theoretical Distribution for every variable regarding manipulators

As far as the descriptive statistics for the non-manipulators is concerned, SGI and AQI variables present the highest mean in the group of non-manipulators. The standard deviation for Sales General and Administrative Expenses Index (SGAI) presents the highest value out of the eight variables (0.367) which implies that the the values of this index for the non-manipulator companies are significantly more scattered among the mean (1.0409) than the other variables.

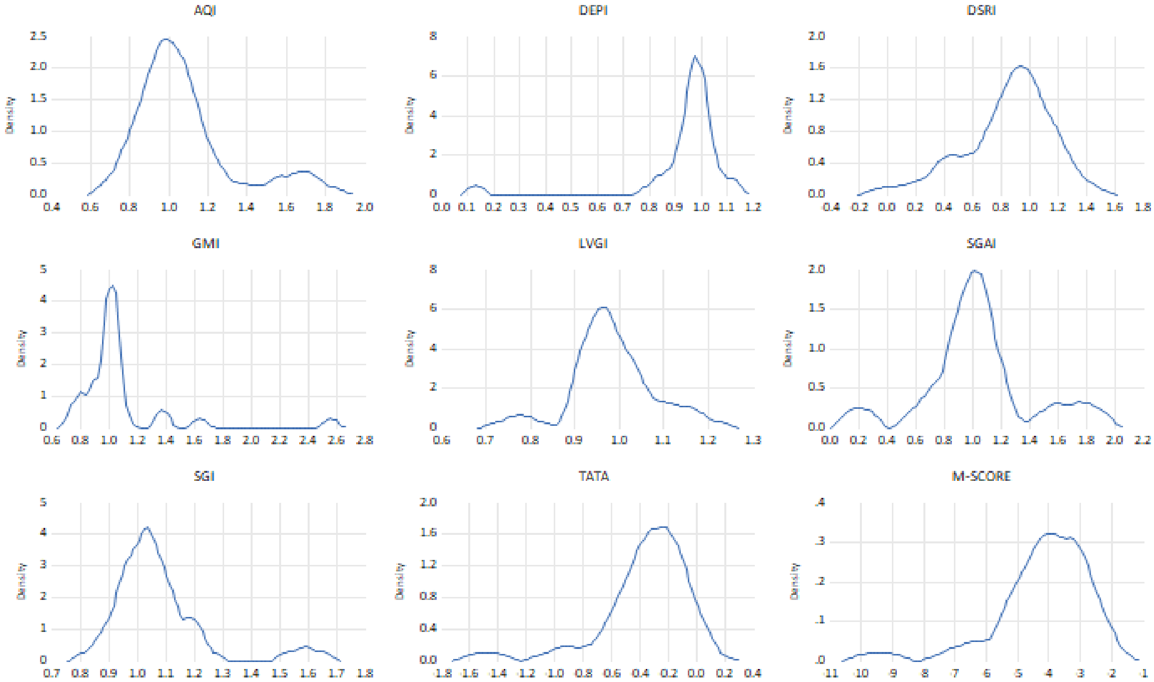
Table 7: Variables descriptive statistics for non-manipulators

	DSRI	*GMI*	*AQI*	*SGI*	*DEPI*	*SGAI*	*LVGI*	*TATA*
Non-Manipulators								
Mean	0,857	1,064	1,071	1,072	0,950	1,040	0,985	-0,357
Median	0,893	1,015	1,018	1,052	0,983	1,004	0,980	-0,281
Maximum	1,366	2,563	1,769	1,632	1,126	1,866	1,198	0,058

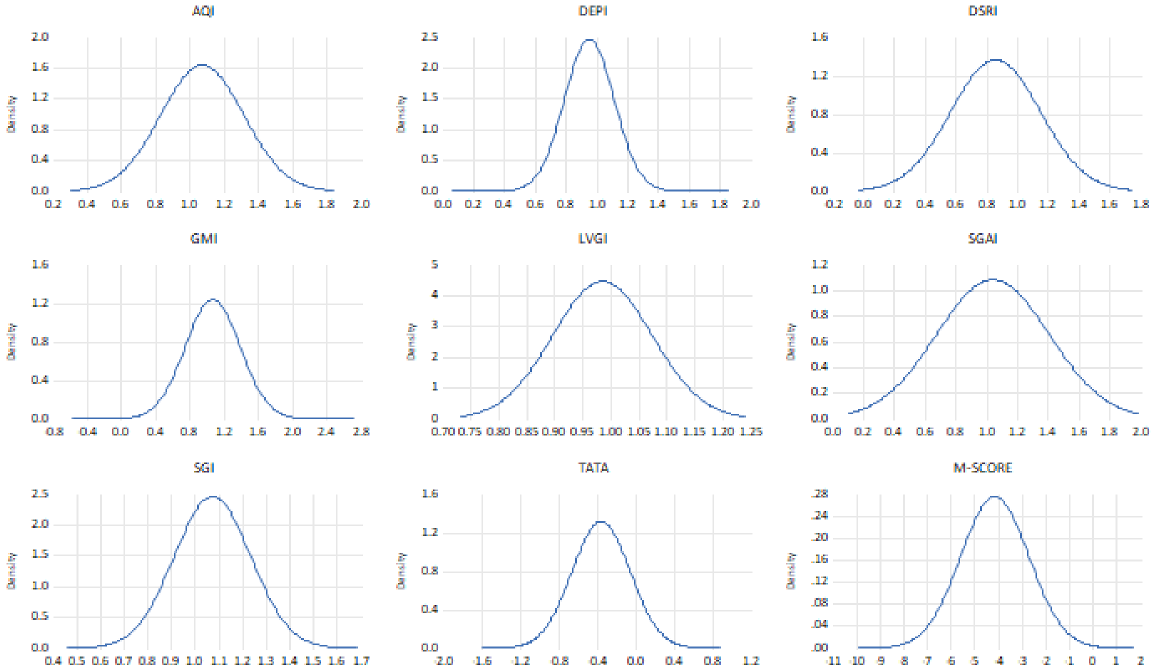
Minimum	0,050	0,741	0,745	0,842	0,133	0,191	0,752	-1,481
Std. Dev.	0,292	0,321	0,243	0,162	0,161	0,367	0,089	0,303
Skewness	-0,781	3,365	1,460	1,968	-4,064	0,190	0,034	-1,813
Kurtosis	3,402	15,849	4,683	7,453	21,384	3,910	4,016	7,254
Sum	28,293	35,123	35,356	35,391	31,354	34,309	32,501	-11,772
Sum Sq. Dev.	2,731	3,293	1,889	0,837	0,833	4,320	0,255	2,931
Observations	33	33	33	33	33	33	33	33

According to table 7, the highest kurtosis value among non-manipulators belongs to DEPI variable (21,384) followed by GMI (15,849). Therefore, these variables' distribution is considered as leptokurtic which associates with Graph 7 that shows the Theoretical Distribution for every variable. Leptokurtic distribution is longer and tails are fatter as depicted in Graph 6. Peak is high and sharp which means that data are heavy-tailed or profusion of outliers. No variable showcases kurtosis value less than 3 which gives the distribution a shorter shape and thin tales. Variables such as DSRI and SGAI present a value of kurtosis around 3 and thus demonstrate a mesokurtic distribution which means that the extreme values of the distribution are similar to that of a normal distribution characteristic.

According to table 7, all variables except for DSRI, DEPI and TATA demonstrate positive skewness which means that the tail on the right side of the distribution is longer or fatter. This shape can be further seen in graph 6 which shows the kernel density distribution for manipulators. DSRI, DEPI and TATA on the other hand, present negative skewness which means that the tail of the left side of the distribution is longer or fatter than the tail on the right side. SGAI and LVGI variables' distributions are fairly symmetrical (skewness value between -0,5 and 0,5).



Graph 6: Kernel Density Distribution for non-manipulators



Graph 7: Theoretical Distribution for every variable regarding non-manipulators

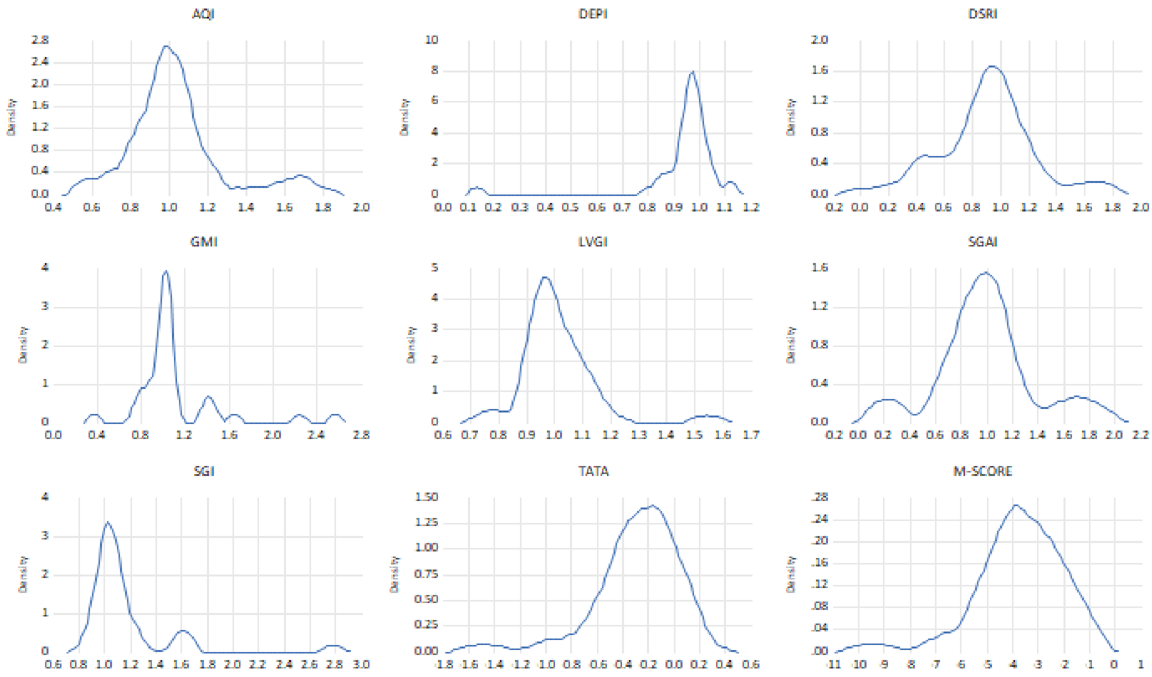
Descriptive statistics for the whole sample shows that the highest mean belongs to SGI variable like manipulators and non-manipulators. GMI, AQI and LVGI follow not very far behind. The largest standard deviation is observed in GMI values while the shortest one belongs to LVGI variable.

Table 8: Descriptive statistics for total sample

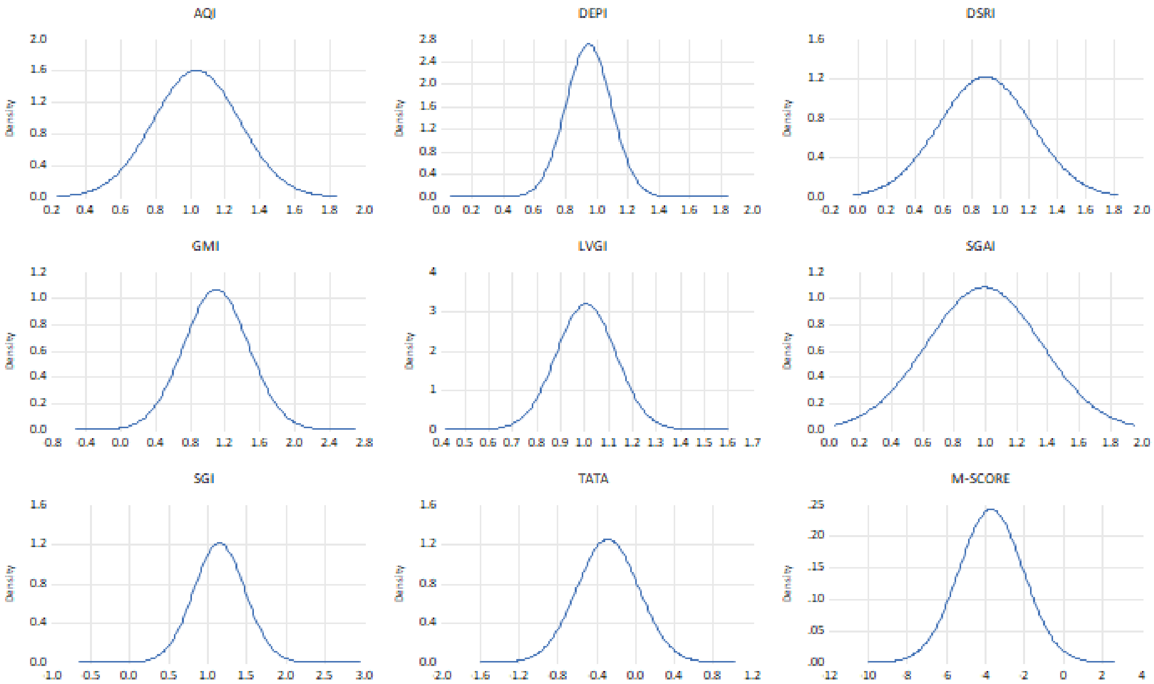
	DSRI	GMI	AQI	SGI	DEPI	SGAI	LVGI	TATA
Total								
Mean	*0,899*	*1,095*	*1,034*	*1,147*	*0,948*	*0,992*	*1,006*	*-0,285*
Median	*0,914*	*1,022*	*1,010*	*1,056*	*0,968*	*0,980*	*0,988*	*-0,241*
Maximum	*1,677*	*2,563*	*1,769*	*2,783*	*1,126*	*1,866*	*1,545*	*0,210*
Minimum	*0,050*	*0,373*	*0,598*	*0,842*	*0,133*	*0,191*	*0,752*	*-1,481*
Std. Dev.	*0,327*	*0,373*	*0,247*	*0,329*	*0,147*	*0,367*	*0,124*	*0,318*
Skewness	*-0,056*	*2,212*	*1,184*	*3,418*	*-4,376*	*0,259*	*1,911*	*-1,541*
Kurtosis	*3,813*	*9,290*	*4,894*	*16,677*	*25,185*	*3,799*	*10,264*	*6,568*
Sum	*35,974*	*43,797*	*41,364*	*45,877*	*37,938*	*39,668*	*40,231*	*-11,385*
Sum Sq. Dev.	*4,169*	*5,417*	*2,387*	*4,208*	*0,842*	*5,256*	*0,603*	*3,951*
Observations	*40*	*40*	*40*	*40*	*40*	*40*	*40*	*40*

According to table 8, the highest kurtosis value among the total sample belongs to DEPI variable (25.185) followed by SGI (16,677) and LVGI (10,264). Therefore, these variables' distribution is considered as leptokurtic which associates with Graph 9 that shows the Theoretical Distribution for every variable. Leptokurtic distribution is longer and tails are fatter as depicted in Graph 8. Peak is high and sharp which means that data are heavy-tailed or profusion of outliers. All variables of the total sample have kurtosis value greater than 3. On the other hand, no variable showcases kurtosis value less than 3 which gives the distribution a shorter shape and thin tales. Variables such as DSRI and SGAI present a value of kurtosis around 3 and thus demonstrate a mesokurtic distribution which means that the extreme values of the distribution are similar to that of a normal distribution characteristic.

According to table 8, all variables except for DSRI, DEPI and TATA demonstrate positive skewness which means that the tail on the right side of the distribution is longer or fatter. This shape can be further seen in graph 8 which shows the kernel density distribution for manipulators. DSRI, DEPI and TATA on the other hand, present negative skewness which means that the tail of the left side of the distribution is longer or fatter than the tail on the right side. DSRI and SGAI distributions are fairly symmetrical while all other variables' distributions are highly skewed (skewness value less than-1 or greater than 1).



Graph 8: Kernel Density Distribution for total sample



Graph 9: Theoretical Distribution for every variable regarding total sample

In order to examine the significance of every variable independently in relation to M-Score which represents Beneish model, least squares regression is formed. The same formula is reiterated for each and every of the eight variables. Therefore, eight hypotheses and a null hypothesis are formed including the variables:

H_0: There is not significant relationship between a variable and M-Score (variable coefficient=0)

H_1: There is a significant relationship between DSRI and M-Score (DSRI coefficient≠0)

H_2: There is a significant relationship between GMI and M-Score (GMI coefficient≠0)

H_3: There is a significant relationship between AQI and M-Score (AQI coefficient≠0)

H_4: There is a significant relationship between SGI and M-Score (SGI coefficient≠0)

H_5: There is a significant relationship between DEPI and M-Score (DEPI coefficient≠0)

H_6: There is a significant relationship between SGAI and M-Score (SGAI coefficient≠0)

H_7: There is a significant relationship between LVGI and M-Score (LVGI coefficient≠0)

H_8: There is a significant relationship between TATA and M-Score (TATA coefficient≠0)

The M-Score in the study expresses the earnings management conducted by the examined companies. In order to test the aforementioned hypotheses, correlation coefficient, least squares regression, r square, t-statistic and p value of the t-statistics are used.

First, the relation of the DSRI variable and M-Score is examined. According to the results of the regression in table 10, the model is not significant at 95% confidence level since the t-statistics is 1.046 and p-value of t-test is 0.302 which is higher than the significance level of 0.05. Therefore, the null hypothesis (H_0) is accepted which means that Days Sales in Receivables Index (DSRI) does not have a significant relationship with the M-Score. Besides, the R square value of 0.028 signifies that the equation explains only 2.8% of the M-Score.

Table 10: Results of regression using DSRI and M-Score

	Coefficients	*Standard Error*	*t Stat*	*P-value*
DSRI	0.838	0.802	1.046	0.302
C	-4.470	0.766	-5.835	0.000
R Square	0.028			

Next, the relation of the GMI variable and M-Score is examined. According to the results of the regression in table 11, the model is not significant at 95% confidence level since the t-statistics is 1.723 and p-value of t-test is 0.092 which is higher than the significance level of 0.05. Therefore, the null hypothesis (H_0) is accepted which means that Gross Margin Index (GMI) does not have a significant relationship with the M-Score. Besides, the R square value of 0.073 signifies that the equation explains only 7.3% of the M-Score.

Table 11: Results of regression using GMI and M-Score

	Coefficients	*Standard Error*	*t Stat*	*P-value*
GMI	1.187	0.687	1.723	0.092

C	-5.016	0.793	-6.3220	0.000
R Square	0.073			

In the next table (table 12) the relation of the AQI variable and M-Score is examined. According to the results of the regression in table 12, the model is not significant at 95% confidence level since the t-statistics is -0.773 and p-value of t-test is 0.445 which is higher than the significance level of 0.05. Therefore, the null hypothesis (H_0) is accepted which means that Asset Quality Index (AQI) does not have a significant relationship with the M-Score. Besides, the R square value of 0.015 signifies that the equation explains only 1.5% of the M-Score.

Table 12: Results of regression using AQI and M-Score

	Coefficients	*Standard Error*	*t Stat*	*P-value*
AQI	-0.824	1.066	-0.773	0.445
C	-2.864	1.133	-2.5287	0.016
R Square	0.015			

Below, the relation of the SGI variable and M-Score is examined. According to the results of the regression in table 13, the model is significant at 95% confidence level since the t-statistics is 2.010 and p-value of t-test is 0.05.. Therefore, the null hypothesis (H_0) is rejected which means that Sales Growth Index (SGI) has a significant relationship with the M-Score. Besides, the R square value of 0.096 signifies that the equation explains only 9.60% of the M-Score.

Table 13: Results of regression using SGI and M-Score

	Coefficients	*Standard Error*	*t Stat*	*P-value*
SGI	1.546	0.770	2.010	0.051

C	-5.489	0.917	-5.986	0.000
R Square	0.096			

Next, the relation of the DEPI variable and M-Score is examined. According to the results of the regression in table 14, the model is not significant at 95% confidence level since the t-statistics is -0.655 and p-value of t-test is 0.516 which is higher than the significance level of 0.05. Therefore, the null hypothesis (H_0) is accepted which means that Depreciation Index (DEPI) does not have a significant relationship with the M-Score. Besides, the R square value of 0.011 signifies that the equation explains only 1.1% of the M-Score.

Table 14: Results of regression using DEPI and M-Score

	Coefficients	*Standard Error*	*t Stat*	*P-value*
DEPI	-1.179	1.800	-0.655	0.516
C	-2.597	1.727	-1.504	0.141
R Square	0.011			

Below, the examination of the relation of the SGAI variable and M-Score is presented. According to the results of the regression in table 15, the model is not significant at 95% confidence level since the t-statistics is -1.125 and p-value of t-test is 0.268 which is higher than the significance level of 0.05. Therefore, the null hypothesis (H_0) is accepted which means that Sales General and Administrative Expenses Index (SGAI) does not have a significant relationship with the M-Score. Besides, the R square value of 0.032 signifies that the equation explains only 3.2% of the M-Score.

Table 15: Results of regression using SGAI and M-Score

	Coefficients	*Standard Error*	*t Stat*	*P-value*
SGAI	-0.801	0.712	-1.125	0.268
C	-2.921	0.752	-3.883	0.000
R Square	0.032			

Next, the relation of the LVGI variable and M-Score is examined. According to the results of the regression in table 16, the model is not significant at 95% confidence level since the t-statistics is 0.400 and p-value of t-test is 0.691 which is higher than the significance level of 0.05. Therefore, the null hypothesis (H_0) is accepted which means that Leverage Index (LVGI) does not have a significant relationship with the M-Score. Besides, the R square value of 0.004 signifies that the equation explains only 0.4% of the M-Score.

Table 16: Results of regression using LVGI and M-Score

	Coefficients	*Standard Error*	*t Stat*	*P-value*
LVGI	0.854	2.134	0.400	0.691
C	-4.575	2.162	-2.116	0.041
R Square	0.004			

Finally, the relation of the TATA variable and M-Score is examined. According to the results of the regression in table 17, the model is significant at 95% confidence level since the t-statistics is 26.408 and p-value of t-test is 0.00 which is lower than the significance level of 0.05. Therefore, the null hypothesis (H_0) is rejected (and the alternative H_8 hypothesis is accepted) which means that Total Accruals to Total Assets

(TATA) has a significant relationship with the M-Score. Besides, the R square value of 0.948 signifies that the equation explains 94.8% of the M-Score.

Table 17: Results of regression using TATA and M-Score

	Coefficients	*Standard Error*	*t Stat*	*P-value*
TATA	5.017	0.190	26.408	0.000
C	-2.289	0.081	-28.424	0.000
R Square	0.948			

In order to further examine the relationship between each variable independently and M-Score, a covariance analysis with the software Eviews is presented. In table 18, the results of the analysis are presented. For every set of variables (two per set) the correlation, t-statistic and p-value of the t-statistic are shown. This table presents in short the results mentioned above regarding the relationship of each and every of the eight variables with the M-Score. According to the findings, only TATA and SGI seem to have a significant relationship with earnings manipulation at 95% confidence level. In the other lines of the analysis the relationship and the significance between the variables are examined. Thus, AQI and DSRI variables seem to have a significant negative relationship since t-statistic is -3.645 and p-value 0.001 which is lower than significance level of 0.05. DEPI and DSRI also seem to have a significant relationship since t-statistic is 2.226 and p-value 0.03. The correlation value is 0.340 which implies a positive relation between the two variables. The table shows that LVGI and SGI are positively related with correlation value of 0.630, t-statistic 5.001 and p-value 0.000.The last set of variables that seem to have a significant relationship according to the covariance analysis is SGAI and SGI. With a correlation value of -0.541, t-statistic -3. 963 and p-value of 0.00, there seems to be a significant negative relation between these two variables.

Table 18: Covariance Analysis between variables and M-Score

Covariance Analysis: Ordinary
Date: 12/08/19 Time: 14:16
Sample: 1 40
Included observations: 40

Correlation t-Statistic Probability Observations	AQI	DEPI	DSRI	GMI	LVGI	M_SCORE	SGAI	SGI	TATA
AQI	1.000000								

	40								
DEPI	-0.096219	1.000000							
	-0.595899	-----							
	0.5548	-----							
	40	40							
DSRI	-0.509020	0.339579	1.000000						
	-3.645413	2.225551	-----						
	0.0008	0.0321	-----						
	40	40	40						
GMI	-0.055986	0.090412	0.250563	1.000000					
	-0.345662	0.559628	1.595469	-----					
	0.7315	0.5790	0.1189	-----					
	40	40	40	40					
LVGI	0.007011	0.059442	0.023598	-0.102943	1.000000				
	0.043222	0.367074	0.145510	-0.637970	-----				
	0.9658	0.7156	0.8851	0.5273	-----				
	40	40	40	40	40				
M_SCORE	-0.124367	-0.105705	0.167236	0.270004	0.064806	1.000000			
	-0.772651	-0.655284	1.045637	1.728621	0.400333	-----			
	0.4445	0.5162	0.3023	0.0920	0.6912	-----			
	40	40	40	40	40	40			
SGAI	0.219571	-0.055206	0.182762	0.131550	-0.130196	-0.179434	1.000000		
	1.387381	-0.340835	1.145922	0.818041	-0.809473	-1.124356	-----		
	0.1734	0.7351	0.2590	0.4184	0.4233	0.2679	-----		
	40	40	40	40	40	40	40		
SGI	-0.246252	-0.212422	-0.181828	-0.218155	0.630154	0.309927	-0.540811	1.000000	
	-1.566230	-1.340037	-1.139863	-1.377988	5.002802	2.009466	-3.963392	-----	
	0.1256	0.1882	0.2615	0.1763	0.0000	0.0516	0.0003	-----	
	40	40	40	40	40	40	40	40	
TATA	-0.034731	-0.160683	0.023433	0.162824	-0.023190	0.973820	-0.120632	0.223101	1.000000
	-0.214226	-1.003556	0.144490	1.017293	-0.142993	26.40796	-0.749093	1.410845	-----
	0.8315	0.3219	0.8859	0.3154	0.8871	0.0000	0.4584	0.1664	-----
	40	40	40	40	40	40	40	40	40

CHAPTER 4

CONCLUSIONS

4.1 Conclusion

Companies have and will always try to find ways to prettify their financial statements and their earnings potential in order to appeal to all stakeholders. Their survival and prosperity depends on the funds from investors, their ability to borrow funds with low interest rate and the satisfaction of their customers. Therefore, when companies go through less profitable or even loss periods, they feel the pressure to seek alternative and sometimes even illegal ways to cover up less favorable financial results. The act of purposefully misstating a company's financial information in order to present a misleading and rather favorable financial image is considered as financial statement fraud.

There have been many different techniques related to financial fraud conducted by companies in the global literature. This study focuses on earnings manipulation as a means of financial statement fraud which constitutes the use of accounting techniques and principles in order to falsely present an overly positive view of a company's financial statements or to hide a seemingly deficient economic position. Some of the most notorious techniques related to earnings manipulation involve tampering with the accruals, the intangible assets, depreciation and amortization or extreme recognition of fictitious expenses.

Many studies have tried to explain the reasons and motivation behind financial fraud. According to recent bibliography, the main culprit can fall into two categories :human behavior and capital market motivations. Some human behavior characteristics may justify the involution of an executive employee in a financial fraud action. Even a company's culture and its working environment may influence the probability of conducting financial fraud. In a strict profit target-centered company, managers might feel obligated to commit earnings manipulation techniques in order to achieve certain benchmarks. Besides, market motivations include a company's high stock price in Stock Exchange Market and low interest rates for cheap funding.

According to the Report to the Nations issued by The Association of Certified Fraud Examiners, 2,690 cases of occupational fraud were discovered in 2018 in companies around the globe, 10% of which refers to financial statement fraud. These fraud cases make up for over $7 billion in total loss. This is why the Greek Law provides for potential administrative and/or criminal sanctions depending on the severity of the fraud.

Due to the severeness of the financial fraud, many researchers have studied different ways and have come up with scientific models in order to examine whether a company conducts financial fraud. Some of the most popular studies involve researchers such as Persons, Green and Choi, Summers and Sweeney, Beneish, Spathis et al., Kirkos et al., Gaganis, Cecchini et al.These respected scientists have developed methods based on Regression, Neural Network and/or Artificial Intelligence models in order to estimate the financial fraud.

This study is based on Beneish model developed by Beneish in a study released in 1999 and has been used by other academics until today to examine the probability of financial statement fraud due to earnings management. According to this model,there are eight variables made from financial statement information that are related to earnings management:

Days Sales in Receivables Index (DSRI), Gross Margin Index (GMI), Asset Quality Index (AQI), Sales Growth Index (SGI), Depreciation Index (DEPI), Sales General and Administrative Expenses Index (SGAI) , Leverage Index (LVGI), Total Accruals to Total Assets (TATA). These eight variables are then multiplied by eight coefficients calculated by Beneish through linear regression. Therefore the M-score model created is shown below:

$$\text{M-Score} = -4.84 + 0.92 \times \text{DSRI} + 0.528 \times \text{GMI} + 0.404 \times \text{AQI} + 0.892 \times \text{SGI} + 0.115 \times \times \text{ DEPI} - 0.172 \times \text{SGAI} + 4.679 \times \text{TATA} - 0.327 \times \text{LVGI}$$

The M-Score represents earnings manipulation. According to his study, Beneish estimates that any company with M-Score -2.22 or above is likely to be a manipulator whereas any company that scores -2.22 or less is unlikely to conduct earnings manipulation.

In this study, the sample consists of some of the companies listed in the General Index of Athens Exchange Stock Market. The total sample is ultimately made up of 40 publicly listed companies. After calculating the M-Score for each company, it was found that 33 (out of 40) companies had a M-Score value lower than -2.22 and thus are categorized as non-manipulators. In the meantime, 7 companies presented M-Score higher than -2.22 and thus are categorized as manipulators. In other words, 82.5% of the sample is considered rather unlikely to conduct earnings manipulation whereas 17.5% of the companies listed in the General Index of Athens Stock Exchange Market is likely to manipulate its earnings.

In order to examine the significance of every variable independently in relation to M-Score which represents Beneish model, least squares regression is formed. The same formula is reiterated for each and every of the eight variables.With t-statistics values of 26.408 and 2.010 respectively it was found that TATA and SGI variables have a significant relation with the M-Score.

A covariance analysis between the eight variables and M-Score was calculated in order to examine the significant relationship between them. Thus, AQI and DSRI variables seem to have a significant negative relationship since t-statistic is -3.645 and p-value 0.001 which is lower than significance level of 0.05. DEPI and DSRI also seem to have a significant relationship since t-statistic is 2.226 and p-value 0.03. The correlation value is 0.340 which implies a positive relation between the two variables. The table shows that LVGI and SGI are positively related with correlation value of 0.630, t-statistic 5.001 and p-value 0.000.The last set of variables that seem to have a significant relationship according to the covariance analysis is SGAI and SGI. With a correlation value of -0.541, t-statistic -3. 963 and p-value of 0.00, there seems to be a significant negative relation between these two variables.

Even though Beneish model examines the probability of financial statement fraud due to earnings management and this study's results regarding seven potential company manipulators are significantly important, the information should be treated very carefully. Beneish model offers a probability of financial fraud and should be therefore used as a supplementary test for auditors, fraud examiners and official regulators. Further evidence is needed before a company can be called responsible for conducting financial fraud due to earnings management. However, M-Score model is a cheap and convenient way for auditing services to serve as an early indication of probable fraudulent action in a company.

4.2 Discussion for Future Studies

Beneish model can be applied to all companies except for those related to financial services. Therefore, more research could be focused on achieving accuracy of the model for financial institutions. In this study, all the banks and credit institutions were left out of the sample due to the fact that M-Score can not provide reliable results when applied on similar companies.

There could also be more research on examining companies that are included in other indexes. This study, uses a sample of the companies that make up the General Index of Athens Stock Exchange Market in 2017-2018. However, the same model could be applied to all publicly traded companies that might belong to other indexes such as Mid cap, large cap or small cap indexes.

In order to test the accuracy and the significance of the results, another model or formula can be used for the same sample and the same period. There are already plenty of models in academic literature that study ways so as to predict the possibility of financial statement fraud. Some studies are based on linear regression while some others use more modern methods of examining a company's financial position such as neural networks or artificial intelligence. Thus, there could be a reiteration of the same sample using another model in order to compare and verify the outcome.

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