Creative accounting, fraud and IFRS in Greece

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Whlist registered as a candidate for the above degree, I have not been registrered for any other research award. The results and conclusions embodied in this thesis are the work of the named candidate and have not been submited for any other academic award.

Abstract

This thesis presents an investigative study of the detection of fraudulent financial statement by applying machine learning techniques. It specifically focuses on the processes of computational intelligence. My research aims to compare the applicability of a relatively inclusive group of machine learning techniques to enable financial statement fraud prediction. More specifically, first, we examine which can utilise algorithms the most given the variegated assumptions about the fraud's classification costs. Second, we discuss which predictors are essential in algorithms for the discovery of fraudulent financial statements.

Furthermore, this thesis examines whether the utilisation of creative accounting decreased after adopted IFRS. In particular, Chapter 1 is the introductory chapter of the research. Chapter two contained a literature review of the accounting environment in Greece. Also, chapter two examines the causes that led to the establishment of Greek legal and accountancy systems. It addresses the association between the accounting and the taxation systems.

Moreover, this chapter offers information on the differences between the IFRS and the Greek GAAP. Chapter three comprises a literature review and theoretical analysis of creative accounting—chapter four refers to the research methods and empirical studies utilised and undertaken, respectively. We present a comprehensive classification and using the critical aspects of the algorithm detection used. We investigated the fraud type and the detection methods' performance for financial statement fraud, analyse the existing fraud detection literature. Specifically, we study the implementation of machine learning techniques, like the Naïve Bayes, Random Forest, Support Vector.

Machine (SVM), Decision Tree, Logit Regression, and K-NN. We followed a comprehensive classification framework of machine learning techniques' application in fraudulent financial statements detection.

Furthermore, Chapter six refers to the effect that IFRS implementation had on earnings management. It emphases the utilisation of creative accounting in the periods before and after the IFRS is adopted. Chapters five and seven address the experimental results of this research. Finally, Chapter Eight is the concluding chapter, and it refers back to the research questions and objectives. Also, it states the contributions and the findings of the study again.

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Abbreviations

ACFE	Association of Certified Fraud Examiners
ASE	Athens Stock Exchange
CPA	Certified Public Accountants
CVSR	Cross Validation Success Classification Rate
DT	Decision Tree
ECB	The European Central Bank
ELTE	Greek Accounting-Auditing Oversight Board
ESMA	European Securities and Market Authority
EU	European Union
FFS	Fraudulent Financial Statements
GAAP	Generally Accepted Accounting Principles
GCBR	Greek Code of Books and Records
GDP	Gross Domestic Product
GNP	Gross National Product
HCMC	Hellenic Capital Market Commission
IAS	International Accounting Standards
IASB	International Accounting Standards Board
IFRS	International Financial Reporting Standards
IMF	International Monetary Fund
IOSCO	International Organization of Securities Commissions
IPO	Initial Public Offering
K-nn	K-Nearest Neighbours
LR	Logistic Regression
NB	Naïve Bayes
NYSE	New York Stock Exchange
OECD	The Organization for Economic Co-operation and Development
P.D	Presidential Decrees
RF	Random Forest
SA	Société Anonyme
SEC	Securities and Exchange Commission
SME	Small - Medium- Sized Entities
SVM	Support Vector Machine

TTRC	Tax Transactions Reporting Code

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Chapter 1: Introduction

1.1 Research Background

The economic scandals of recent decades (Enron, Worldcom), the competitive economic environment, and business executives' pressures to achieve higher and higher goals signal a new threat to the financial system: the falsification of accounting statements.

Accounting scandals discovered more frequently in the last decades—these scandals mainly based on the falsification of financial statement fraud. Also, many firms declare bankruptcy due to altering, falsifying or manipulating the accounting records. According to the ACFE announcement on occupational abuse and fraud, an average of fraudulent financial statements practised by investigation respondents is valued at over the U.S.$1 million (ACFE, 2020). Serious difficulties caused in the economy and the market due to misleading financial statements. These often force investors to bear large losses. The customers mistrust the market, litigation, and accounting systems. Moreover, the organisations and individuals connected to financial report fraud experience embarrassment.

So, firms' financial statements play an essential role in providing thought, providing insights into a company's past, its present, and where it headed. The financial statements that are issued by firms with integrity fairly represent their financial position. Generally Accepted Accounting Principle (GAAP) forms the foundation of the creation of these financial reports. These principles influence accounting in transactions.

Consequently, a necessity arises for regulators, lenders, and investors to examine how they will distinguish fraudulent financial statements more successfully.

Computational intelligence techniques are a promising solution to problems of forecasting falsified financial statements and bankruptcy. The main goal is to create algorithms that, through empirical knowledge, provide the possibility of automated solutions to complex problems.

Some researchers try to detect financial statement fraud by using financial ratios combined with computational intelligence methods. More specifically, researchers use the predictive ability of financial ratios to detect fraud.

This thesis aims to detect factors (ratios) that can detect financial statement fraud combined with computational intelligence techniques. This thesis introduced the basic definition of financial ratio and accounts, and we continue with the models used mainly to identify fraudulent financial statements.

1.2 Contributions of the thesis

This thesis gives more intuition into the implementation of IFRS accounting quality and creative accounting in variegated regulatory and cultural contexts. This research is also essential to ethics setters, watchdogs, and academics. We choose to analyse the financial statements of Greek enterprises for the following reason:

As a European Union member, Greece should apply the accounting, auditing, and financial reporting requirements, determined by European Union Regulations and Directives as transposed into Greek regulations and laws. A new accounting law (4308/2014) introduced in 2015. Law 4308/2014 has many differences in financial reporting requirements. Law 4308/2014 introduced the different types of companies depending on their number of employees, size in terms of annual turnover, and total assets. Under this law, banks, listed companies, financial institutions, and insurance companies must adopt IFRS as implemented by the EU to prepare their financial statements. All other firms should apply Greek GAAP, which differs from IFRS.

Before the law, 4308/2014, firms in Greece apply the accounting law 1041/1980 until 2014. Consequently, Greece used an accounting law until 2014, too old and had many gaps. Iatridis and Rouvolis (2010) noticed that the degree of earnings management in

Greece-based firms became lower after implementing IFRS. Nevertheless, two years only were taken into account in their dataset (a year prior and post-implementation of IFRS), although the research utilised 14 years.

Investigating earnings management's use in Greece in the periods prior and post-implementation of IFRS is essential, as raised enticements provided to manage earnings in the Greek market.

This research investigates the connection between the increased earnings quality and IFRS implementation in Greece and earning management employment before and after implementing IFRS. This research gives a detailed juxtaposition of variance associated with Greece GAAP and IFRS to offer a thorough understanding of this transition's effect. This thesis is the first research in the accounting quality of published financial reports for fourteen years, and no recent comparison is available. Also, the first research that observes the influence of implementing the IFRS in financial statements for eleven years (the start year being 2005).

The decision to direct the focus to a single country study (using only Greece in this study) is in line with Weetman (2006) study. This study encourages single country research authors to identify and discuss the country-specific framework. It also referred to that country-specific researches assisted for more comparative researches on a more comprehensive geographical basis. The findings would also be interesting to the countries that may, in the future, adopt IFRS. Furthermore, the survey presents useful awareness of stock markets' regulators to the degree of compliance with accounting ethics by a firm and its effects on the shareholders' observations.

1.3 Research Questions

This thesis examines the following survey issues:

Q1: Which financial ratios are associated with FFS detection?

Q2: What is the predictive ability of financial ratios on FFS?

Q3: Can a computational intelligence framework be used for FFS detection and prevention?

Q4: Are financial reports in Greece reliable? Have there been any changes regarding the quality of accounting post-implementation of the IFRS in Greece?

1.4 Thesis Organisation

Chapter two reviewed the Greek accounting system and factors that led to Greek accounting and legal systems. This chapter highlights the dissimilarities of the GAAP in Greece and IFRS and the relationship between Greek taxation and accounting.

Chapter three contains a literature review and theoretical analysis of creative accounting. In particular, chapter 3 divided into seven sections. Moreover, in this chapter, we summarise the relevant prior research in financial fraud literature. Pertinent theories of economics and corporate governance are analysed to theoretically study the subjective, objective, and conditional characteristics of the causes of fraudulent financial statement.

Chapter four addresses the first three of the four research questions. Also, this chapter refers to the research methods and empirical analysis. Specifically, various machine learning techniques include the decision tree, Naive Bayes, Logit Regression, Random Forest, K-Nearest Neighbours, and the SVM. We follow a comprehensive classification framework of machine learning techniques useful in identifying fraud in financial accounting.

Chapter 5 addresses the experimental results outlined in Chapter 4. Specifically, we analyse the factor importance and the prediction performance of machine learning techniques’ application. Moreover, we draw a comparison between these methods and factors.

Chapter 6 refers to the special effects of the application of IFRS on earnings management. This chapter, which has five sections, reports creative accounting use before and after implementing the IFRS. In particular, it considers if there was a reduction in management earnings following the implementation of IFRS.

Chapter 7 refers to the experimental results of Chapter 6. This chapter also refers to the effects of comparing the GAAP in Greece and the IFRS period.

Chapter 8 discusses the study questions, goals and summarises research results and their contribution to knowledge. It also highlighted the constraints encountered in the course of the research and valuable future study recommendations.

Chapter 2: Accounting Environment in Greece

2.1 Introduction

This chapter reviewed the literature on the Greece tradition that led to the development of the system of accounting and dissimilarities between Greece accounting other countries. Chapter two also offers essential material on the Greek accounting system's factors in the FFS and IFRS's implementation in Greece.

2.2 The Greek Economy

In 2001, Greece started using the euro, as the country then met all the economic standards needed. The years that followed led Greece to economic growth. For the years 1993-2007 Greek economy has dramatically expanded. During this period, many infrastructure projects as Greece took over to organise the Olympic Games in 2004. The construction industry in Greece had a significant development in the whole country. Greece's citizens enjoy an increased standard of living and a very high index of human development, ranking it 32nd in the world in 2019 (Human Development Reports 2020). However, recent years' recession reduced GDP from 94% of the EU in 2009 to 67% for 2017-2019 (Eurostat 2020). Real per capita consumption also fell from 104% to 78% of the EU average.

Nevertheless, things changed from 2009 onwards. To a certain extent, because of the international economic crisis, it has been evident that Greece is dealing with critical financial problems. In 2010, the country's debt came up to 147.3% of the GNP and its deficit to 10.4% (OECD, 2011). Spending, mistakes made in management, and structural problems, all of which had lasted for many decades, resulting in the debt crisis mentioned above. The government implemented institutional reforms and severe austerity measures to deal with this issue. The impact of this crisis is mainly visible in Greece's private sector due to the mounting unemployment and radical labour market reforms there, which involved a massive reduction in minimum wages and the full decentralisation of the wage bargaining process.

As a result, Greece had to resort to extreme exterior borrowing from EU countries, the ECB and IMF. These actions limited financial policies to be implemented significantly (The Fund for Peace, 2011). The research carried out by the World Economic Forum states that the most critical problems related to Greece free enterprise are corruption, bureaucracy, employment tactics, the inconsistency of policies, taxation policies, assess to loan, weak organisation and deficiency in the dedication of the personnel (Schwab; World Economic Forum, 2010). The research also highlighted that decreased effectiveness of impedes development. Powerful associations, non-liberal trade policies, licensing criteria for many business and corruption hinder entrepreneurship in Greece. Under these circumstances, the country needs to continuously reduce its debt and, consequently, return to a path of economic development that can achieve via privatisations, disbursement of state funds and strengthening market reforms (OECD, 2011).

Economic investments and growth can boost to generate jobs, enhance the public finances' stability and, consequently, facilitate a social safety net that is effective in forming the crucial steps that can allow Greece to recover from the economic crisis' profound social costs, as stated by the OECD (economic Surveys – Greece, 2016, p. 3) in its report of 2016. Also, economic Surveys – Greece, 2016, p. 3 indicates that poverty has increased since the crisis (for example, due to increased unemployment and reduced wages). The economic crisis has affected one-third of the people belonging to the population. Therefore, tackling inequality and poverty is an urgent policy priority in Greece.

This survey perceives the necessity of recovery strengthening in 2017 through substantial external demand benefit investments and jobs and ongoing reforms. It emphasises the need for successful negotiations to focus on public debt sustainability in improving the economic outlook.

However, significant risks persist. Not only can the credit crisis continue, thereby undermining domestic demand, but low activity can also compound due to a decrease in lesser growth in the remaining part of the European area and global trade, which is the destination of one-third of the Greek exports.

The research mentions that significant problems could also be posed for Greece's economy by the refugee crisis, mainly if the EU's contribution is insufficient. Preliminary estimates have stated that the cost of refugees' influx was approximately 0.4% of the GDP in the year 2015.

Angel Gurría, the Secretary-General of OECD, while presenting some aspects of the survey in Athens, stated that Greece had experienced an unpleasant adjustment, resulting in the country's confronting a demanding economic and social stance. Sustained recovery can achieve by making more investments in infrastructure and liberalisation of the network industry. Can be channel EU funds to research, education, innovation, information and communication technology to improve and facilitate economic growth.

Therefore, according to the survey, the necessary resources will require to be reallocated from the savings that have been generated elsewhere, for instance, from pensions, tax collection improvements or defence expenditure. Subsequently, it should focus the pension reform on aligning benefits and contributions, alleviating the burden placed on those who are the most vulnerable and reducing special regimes in a better manner.

For instance, investing to a greater extent in logistics and infrastructure would sustain the exports crucial to making continuous improvement easier. Setting network industries free would enhance both the quality and quantity of investments. The structural fund of the EU should be utilised more fruitfully to boost the flow of investment to the fields of survey, education and ICT for possible perfection of skills.

The OECD report states that, so far, the process of adjustment has heavily depended on labour markets and fiscal measures. Moreover, it mentions that, in the meantime, enough progress has not achieved concerning product market reforms. The product market reforms, which presented during the crisis, have slowly progressive, having been undermined by the implementation's weakness, and have largely retained the position of monopoly power. The enhancement of administrative capacity, clear communication about the expected benefits provided to the general public and the policy changes' more substantial ownership would improve the new improvement programme's effectiveness.

Tax evasion is common in Greece, and, therefore, the incomes required to support social policies reduced. OECD (economic Surveys – Greece, 2016, p. 3) stresses the need for broadening the tax base while strengthening tax administration, giving it more autonomy and allowing it to facilitate the resources for the conduction of improved enforcement and audits.

Bank recapitalisation needs and the weakness of economic growth have increased Greece's already high public debt. According to the OECD (economic Surveys – Greece, 2016, p. 3) research, coming to an understanding with creditors about significant extending maturities and repayment grace phases may guarantee low and stable gross economic necessities in the long run and decrease doubt.

2.2.1 The Greek Economy till 2020

The pandemic covid-19 in Greece has effectively limited inflexions, and the economy has been hit hard as all the world countries. Travel restrictions, containment measures, high uncertainty and social distance decrease the production and tourist demand (OECD 2020). Also, this situation increases unemployment. The government gave economic packages to support the health system and the sectors (such as tourism), which were shocked by covid-19.

The Greek economy before covid-19 had been expanding for the last three years. The average annual growth is 2%. The exports of goods and tourism supported yearly growth. Also, the structure reforms helped the Greek economy to recover. In the last years, Greece has expanded its fiscal targets, and the current account deficit has decreased. Better control of expenses and increased revenues lead the country before covid-19 to sustained and substantial primary budgets surpluses, rebuilding fiscal credibility (OECD 2020). Greece returned to bond markets. The economy is more open before covid-19.

When covid -19 recedes, Greece can focus again on a programme medium-term transformation to reinvigorate its recovery with more substantial and inclusive growth (OECD 2020). The Greek government has to success in four policy objectives after covid-19. The first goal is to achieve sustained economic recovery, and the second goal is to raise long-term growth; the third goal is to protect the economy by covid-19 and improve inclusiveness.

2.3 Changes of accounting regulations

2.3.1 Changes of the accounting system.

Established in 1980, GAAP in Greece through the presidential Decrees required Société Anonyme (SA) and private limited company to compulsory organise and submit balance sheets.

The law 1041/1980 was in effect until 2014. A new law passed through the Parliament on November 20, 2014, introduced a new Greek GAAP meant to impact the fiscal year beginning in January 2015. The law mandated that it would fully incorporate the accounting part of the EU-coded Directive 2013/34. This new law also made significant changes to records maintenance and replaced the tax reporting code.

Moreover, stopped some specific law requirements 2190/1920 and law 3190/1955 about financial reports preparation for insurance firms and economic institutions accounts. Furthermore, Greek GAAP that exists currently were also abolished, along with other provisions. Provisions in law 2065/1992 are related to reassessment of real estate and the law that controls tax machines' associated matters. However, this did not introduce any new changes into the old regime, as the said law has defined it—the new provisions aimed at eliminating the TTRC requirements. The new requirements also depend on authorised bodies to implement applicable measures to audit transaction activity.

In this context, the new conditions' overall concept is to rely on the legal bodies to make proper protection possible (without stating their exact nature beforehand). This will result in accomplishing their transactions and the second one's association to the entries that have to do with accounting. Consequently, it depends on legal entities to implement proper methods to indicate their overall transactional activity easily by potential audit and make sure that it acts in line with the new regulation.

2.3.2 Accounting and auditing profession.

Until 1956 when the CPA Institute was designed and became operational, audits carried out by law 2190/1920 on public limited firms' financial reports were purely a walkover. Greeks specialists on commercial law noted; "the audit of a public limited company is, in our country, a complete formality, constituting a mockery of the state as well as of shareholders and all other interested parties, because, as is well known, in reality, the auditors engaged by the General Assembly of shareholders limit themselves to signing the audit report prepared for them by the board of directors."

While professionals didn't do proper auditing before signing audit report as provided by law 2190/1920, this led to the development of the Institute of CPA in 1956 with law 3329/1955 to conduct significant public-limited audits including small and medium scale companies. The law specifies the non-participation of the auditor in the financial affairs in the firm audited. Moreover, the conflict of interests' problem was also present. The auditors were included in and were provided remunerations by the firm's managers (as shareholders' General Assembly concurred with managers' proposal). After auditing their act, established relations of dependency between the auditors with auditing.

To create a structure for conducting a significant inspection of public limited firms, the state established the Institute of CPAs, which begins operations on November 19, 1956, to remedy the unacceptable condition, leading small and medium audits to large-scale public limited companies. The law stipulates that the auditor would not be involved in ascertaining his/her reward or have any firm's financial concerns.

Professional questions were allocated to the Administrative Committee, with proficiencies with the following clearly: "Certified Public Accountants are not considered civil servants but as exercising a public function. In the discharge of their professional duties, Certified Public Accountants are independent; any intervention whatsoever in their work prohibited. The direct communication between Certified Public Accountant and the audited party for the purpose to determine compensation is prohibited".

Strict rules instituted by the Certified Public Accountant's function (CPA) prevent an auditor from remaining in a firm for more than five years to prevent the auditor from developing a personal relationship with the firm. They have instituted these regulations following the guidelines of English Chartered Accountants, which acted as advisers of the Institute of CPA's without meddling in Greece adoption of the regulatory and legal framework, thus facilitating Greek Audit Standards. Due to Greece law associated with public-limited companies, revised these standards in 1979 to conform to international auditing ethics.

The CPA comprises specialised auditors that enjoy individual independence and audits both private and public organisations and all kinds of businesses. The CPAs' accounting principles to audits between 1993 and 2004 laid down by the Institute of CPA in line with the simple ethics of IAS. CPAs henceforth utilises IAS since 2005.

The accounting and auditing standard oversight board, founded in 2003, controls audits' quality executed by CPAs and other activities carried out by CPAs.

The Greek rule was synchronised with the European Parliament's requirements in 2008 to provide the conditions for procuring a practising license, maintain CPAs public register, adherence to ethics by specialised accountants, adhere to IAS ethics and civil obligation.

2.4 Institutions

2.4.1 Legal system

The most noticeable trait of business organisations in Greece is that they have to function in an austere legal frame. The financial statements have to comply with this system. Sadly, the Greek rule (rule on tax and law that has to do with Greece's economic development) gives many chances to put creative accounting into practice. Although accounting regulation in Greece is quite thorough, creative accounting is often put into practice by taking advantage of the law and GAAP flaws or infringing them. Businesses in Greece operate and prepare their financial statement within a strict legal structure. While the Greek law offers numerous creative accounting opportunities, creative accounting violates these laws by exploiting the GAAP flaws and the law. This observation has led some to propose in-depth accounting instruction single-handedly cannot eliminate the problem; a statement reinforced by Blake & Salas (1996) conducted in Spain where detailed accounting regulations are also in place.

Corruption issue in Greece occurs due to many factors' confluence, including weak law enforcement, audits shortage, behaviour policies deficiency, lack of transparency in the government's endeavours, uneffective bureaucracy, scarcity of punishment on behalf of the government, as well as overall flexible strengths and shortage in the consciousness of the public..

2.4.2 Taxation system

Inman, (2012) reports that corruption and tax evasion are a significant problem in Greece, where politicians evade tax worth €30 billion per year revenue (The Economist, 2012). While political corruption is considered a substantial problem in Greece, its importance may have intensified by the international media, as some observe.

2.4.3 The ASE

The ASE located in Athens. The ASE started trading in 1876. The following five markets operation the ASE: controlled markets (securities, derivatives, alternative, carbon and OTC).

In a regulated securities market, shareholders can do business on EFT, bonds, and stocks, e.t.c. We adopted the significant indices of ASE with over 30; Large Cap (FTSE 25), Composite Index (GD), Global Traders Index Plus (FTSEGTI), the Factor-Weighted Index (FTSEMSFW), Mid Cap Index (FTSEM) and Market Index (FTSEA).

Furthermore, the HCMC controls the transactions for the listed companies. In 2017, representing 213 companies on ASE with 221 shares. The security market comprises 208 shares (200 firms), while the alternative market includes 13 shares (13 firms).

ASE has played a vital part in Greece economic growth in the latter part of the 20th Century. The stock exchange market in Greece was affected by the stock market crash of 1999, which was associated with Greece's accession into the monetary and economic union. In this period, many Greek households bought and sold stocks and the active investor codes on the ASE reached about 1.5 million. The general index recorded a new high every day, with the data recorded on any given day being higher than that in the previous day. Therefore, many Greek families believed that they had figured out a way to secure an annual income for the rest of their lives. However, in September 1999, the general index started to decline, and this trend continued for many years. As a result, many stocks listed on the ASE lost their value. Many of these stocks proved to be "bubbles", meaning that the stocks were unrelieved, and many of these companies had not projected their value but only had an attractive stock market image. From 2000 onwards, and later 2006, the ASE was considered a developing and advanced developing market. In 2007, the general index came close enough to 1999; however, the broad index decreased again between 2008 and 2012. The year 2015 was ASE's one of the most critical years. Following the debt crisis and capital control implementation on June 3, 2015, the ASE was closed and later crashed again after being reopened on August 3, 2015, leading to an index lost of over 16% while bank stocks lost was 30% revenue the day's trading.

In Greece, the requirement of financial reports has recently drawn attention following raised firms listed on ASE and efforts to maximise profit by reducing taxation. Rising request for greater transparency, consistent incorporation of information into financial statements by the public is mounting.

2.4.4 The HCMC

To ensure organised and effective operation and protection of the asset market, the HCMC (HCMC,2015) created as an authorised body in 1969/91 for national economic growth. Equipped with the European and Greek legislation, the HCMC's management and staff have functional and individual independence to realise its objectives. It is not financed with the state budget. The Board of Directors drafts the HCMC budget for approval by the Finance Minister. Reports of the HCMC activity on the capital market are submitted Finance Minister and President of the Greek Assembly. HCMC operates within the ESMA framework and auspices as a member.

As part of the IOSCO, the HCMC (HCMC,2015) completes two-sided and multifaceted contracts to exchange vital information with other authorities.

The HCMC being in charge of the proper application of capital market legislation, is also obligated to engage authoritatively in establishing capital market structure rules. The HCMC supervises the foreign and Greek firms, among others, that offer new investments' and collective investments' undertakings, investment services, their managers and the listed companies regarding their takeover bids, transparency obligations, corporate events, financial statements and shareholders and their responsibility on notification of significant holdings. HCMC (HCMC,2015) also oversees transaction such as the actions of the persons who possess insider information and market abuse issues and the supervised persons’ compliance with money-laundering legislation.

Supervision provided by HCMC (HCMC,2015) concerning the regulated markets, shareholder reward scheme and clearinghouses. It also examines international and domestic developments, certifies the market participants’ professional suitability and conducts research when necessary. Also, it investigates receiving the investors’ complaints.

While the HCMC (HCMC,2015) can sanction and measures like warnings, suspension and fines of license for violators of capital market legislation, it can also initiate criminal proceedings to those involved in serious criminal offences with capital market structure.

2.4.5 Corporate governance

It maintained that reliable company control significantly limits creative accounting practice (Shah, 1998). Moreover, as presented in the research conducted by Dechow and Skinner (2000), the firms under the security and exchange commission (SEC) likely have weaker governance structures. They are unlikely to possess an audit committee, greater propensity to be dominated by an insider in the board, with CEO who is the founder evidence by the researchers proposes a weak governance structure in a company is possible to participate in the earnings management. Due to strict family participants in the board of the majority of Greek firms, small companies have also followed suit, thus increasing fraud chances (Beasley, 1996; Dechow et al., 1996; Klein, 2002).

2.4.6 Conclusions & Discussion of the accounting environment in Greece

So far, we descriptive the legal framework that existing in Greece till 2014. Since 2015, Greece's accounting and auditing legal and regulatory framework based on three essential laws: the whole system's pillars.

Law 4308/2014 is the first pillar and refers to the application and the adoption of the keeping of accounting records and the accounting system. (Government Gazette A 251/24.11.2014). This law also refers to preparing financial statements and adapting accounting records to Greek actuality provisions (Dritsa 2019). This law issued in 2015

Law 4449/2017 is the second pillar and refers to the auditing framework. This law has the central axis "On the statutory audit of annual and consolidated financial statements and public supervision of the audit work and other provisions" (Government Gazette A 7/24.01.2017). Also, this law refers to the responsibility of the auditing profession. It also extends to corporate governance. This law issued in 2017.

Finally, is the law 4548/2018 as published the third pillar. This law refers to "reforming the law of Societies Anonymes" (Government Gazette A 104/13.06.2019) and issued on January 1 2019. This law also replaced the previous law (law 2190/1920), which was too old.

As we can conclude, Greece try to consolidate the European Directives in the national legislation. Also, Greece tries to modernisation and update the accounting framework in modern trends.

This thesis investigates the consequences in the financial statements with the previous law. This research tries to identify the gap if applying the earlier rules in financial statements presents a relative view and the consequences in the economy. This research will also help compare the results in firms' regulatory framework and the syntax of published financial statements according to the three pillars of new accounting law.

2.5 Accounting Regulations

2.5.1 Accounting regulations under the domestic GAAP

The accounting law has lately changed in Greece. The law's provisions adopt the IFRS's rules established for SMEs and have many similarities concerning the initial measurement and recognition of assets and liabilities. Some fundamental changes introduced by the new law in the accounting principles include;

- **Leases**

Operating and finance leases have different accounting. All leases considered operating leases under the Greek GAAP upon recognition with no disparity between operating and financial leases. The leaseholder (lease) in a financial lease assumes both ownership risks and benefits. Thus, a finance lease revealed upon its recognition of liability and asset on the balance sheet. As part of the lease agreement, the company can devalue the asset's value yearly and subtract the interest the company charged with. The adoption of IAS 17 affected debt cost because it increased the claim's expenses and the long-term debt revealed in the balance sheet and income report.

- **The intangible assets' recognition**

Different criteria for intangible assets' recognition under the new law are adopted.

- **Depreciation charges**

The fixed assets with a defined useful lifespan depreciate over their useful economic life. Depreciation starts when ready-to-use assets are available. The entity's management is responsible for choosing the depreciation method, reflecting the pattern in which it expected that assets' financial benefit utilized in the best way possible.

- **Impairment loss**

It measured fixed assets based on cost tested for impairment where impairment indicated. Impairment losses occur when an amount is carrying an asset is smaller compared to its recoverable amount. Impairment loss acknowledged in profit and loss may be reversed provided circumstances arises terminated. However, fixed asset after reversal cannot exceed the value without impairment. More so, it should not change impairment loss if it is for goodwill.

- **Inventory**

Under the law, the inventories initially recognised at the acquisition cost. Accordingly, the inventories' cost shall incorporate the total expenditure required to direct them towards their present location and condition. With significant duration needed to prepare an inventory for use, inventory cost attributable to this inventory included. Consequently, following immediate acknowledgement, can assess the record at a lesser cost.

- **Deferred taxation**

The also introduced deferred taxation to the Greek GAAP, where entities may recognise deferred tax asset or deferred tax liability in their financial reports.

- **Alternative measurement of liabilities and assets at fair value (the fair value option)**

Provides substitute requirement connected to asset and liability evaluation post cost recognition.

- **The obligation of financial statements' preparationbased on an entity's size**

Depending on the classification of an entity as small, medium or large, the law's provisions added particular financial report preparation simulations.

2.6 Greek GAAP and IFRS differences

The Greek law does not recognise or consider fair value models, deferred tax, investment properties, biological assets, assets held for sale and biological produce. Properties and land can only be revalued every four years, according to government indices. The government also indicates the remuneration rates and devaluation of assets.

Exploited, along with the procurement costs, are interest and start-up cost during the construction of properties. While proposed dividends acknowledged as liabilities, scholarships by the government recognised within shareholders equity.

2.7 Conclusion

GDP falls by 26% following economic despair; it predicted that the Greek economy would grow again in 2016 and 2017; however, it stressed that it would take time to make a full recovery. Although competitiveness has improved markedly, investment and exports are still feeble. Therefore, 25% of job loss occur despite the modest that has happened since 2013. This has forced many into poverty with an increase in income inequality. The budget position materially improved by the tax and benefit reforms; however, the adjustment burden is irregular with a high public debt rate. Credit creation options are still reduced due to the high level of underperforming loans on banks, thus reducing loans request.

Chapter3: Literature Review and Theoretical Analysis of Creative Accounting, Fraud and fraudulent financial statements

3.1 Introduction

This aspect of the study reviews related works on fraud, creative accounting and fraudulent financial report. This chapter begins with definitions of fraud, creative accounting, and fraudulent financial statements and explains their relationship (Section 3.2). Section 3.3 shows the classical theories on the determinants of fraudulent financial information. Section 3.4 shows the profile of accounting scandals. Section 3.5 presents the components of financial report fraud as well as the parties involved in creative accounting. Section 3.6 offers the reasons and motivations for creative accounting. Specifically, we analyse manipulation practices, the methods and the opportunities for creative accounting and address why financial frauds occur. Finally, we offer conclusions in Section 3.7.

3.2 Exploring Terms

3.2.1 Creative accounting definition

The terminology of creative accounting used widely—no agreement reached on its exact definition. There is a widely used definition that was embraced by Mulfors and Comiskey (2002) in the U.S.A. with a quit smaller intention that practised in the U.K. In the following table, the two representative definitions of creative accounting presented.

Table 1: Creative Accounting definitions

Year	Definition	Authors
UK		
2005	'The exploitation of loopholes in financial regulation to gain advantage or present figures in a misleadingly favourable light.'	Oxford Dictionary of English
USA		
2002	'All steps used to play the financial numbers game, including the aggressive choice and application of accounting principles, both within and beyond the boundaries of generally accepted accounting principles, and fraudulent financial reporting. Also included are steps taken toward earnings management and income smoothing.'	Mulford andComiskey (2002)
Definition Preferred		
2011	'Using the flexibility in accounting within the regulatory framework to manage the accounts' measurement and presentation so that they give primacy to the interests of the preparers, not the users.'	Jones (2011)

United States meaning of creative accounting includes fraud which is omitted in the U.K as it takes for granted the use of accounting flexibility. This thesis adopts the definition of creative accounting of Jones (2011). As Jones (2011) argued, "the flexibility in accounting opens the door for many different methods of creative accounting". Thus, it perceived as legitimate accounting flexibility use following the preparers' interests, hence not illegal. Creative accounting utilizing firms are not violating the law, as they use accounting flexibility to promote their interests.

Creative accounting formed by taking advantage of the present governing system's ambiguities to work towards the interest of the "preparers" and not that of the "users". Economic reports of listed firms in Europe demanded to put forward account report fair and just. In many countries, there is a dominant belief that accounts must truly depict economic reality. The users are assumed to provided with a series of financial statements that define financial reality. On the contrary, creative accounting favours the preparers' interests (for instance, managers). This is likely to happen because of the fundamental economic need to adapt to give a precise account image.

No creative accounting occurs with inflexibility, as one of the ultimate purposes of accounting is to offer shareholders vital facts that ensure shareholders create economics-related decisions regarding shares. While regulatory structure varies in different countries, the framework sets aim to provide an accurate and fair view to shareholders. More so, elasticity offers managers creative accounting. While managers may not break laws, they deviate from basic accounting ethics and maybe participating in the fraud.

3.2.2 Fraud Definition

The limit between fraud and creative accounting can not always be distinct. The courts or regulatory authorities usually decide fraud. However, as previously stated, companies use creative accounting whilst ending up getting involved in committing fraud. Thus, it is essential to define fraud and analyse the difference between creative accounting and fraud. No clear definition of financial fraud exists; therefore, the table presents some definitions of fraud. These different definitions also show the multidimensional scope of fraud and the different perceptions of fraud.

Table 2: Fraud Definitions

Year	Definition	Authors
1988	"A false representation or concealment of material fact to induce someone to part with something of value".	Sawyer (1988).
1999	"A knowing misrepresentation of the truth or concealment of a material fact to induce another to act to his or her detriment."	Black's Law Dictionary, 7th edition (1999)
2005	"Leading to the abuse of a profit organization's system without necessarily leading to direct legal consequences".	Phua, Lee, Smith andGayler (2005).
2006	"A deliberate act that is contrary to law, rule, or policy with the intent to obtain unauthorized financial benefit".	Wang, Liao, Tsai and Hung (2006).

Fraudulent financial reporting		
1995	“Fraud comprises both the use of deception to obtain an unjust or illegal financial advantage and intentional misrepresentations affecting the financial statements by one or more individuals among management, employees, or third parties. Fraud may involve: o Falsification or alteration of accounting records or other documents o Misappropriation of assets or theft o Suppression or omission of the effects of ıs from records or documents o Recording of transactions without o Intentional misapplication of accounting Wilful misrepresentation of transactions or an entity’s state of affairs.”	Auditing Standards Board, Statement of Auditing Standard, SAS 110 (1995)
Definition of fraudulent financial reporting (preferred)		
2011	"The use of fictitious accounting transactions or those prohibited by generally accepted accounting principles gives the presumption for fraud which becomes proved after an administrative or court proceeding."	Jones (2011).

3.2.3 Types of fraud

While used creative accounting within the regulatory structure, fraud works outside the regulatory framework.

In every country, fraud’s definition differs. However, it essentially comprises a violation of the regulatory framework and breaking the law. Individuals or management can be involved in committing the act of fraud. In the case of individuals, accounting fraud would, in general, affect the theft of assets, such as cash or inventory. On the other hand, in the case of management, it also includes the crime of preparing fraudulent financial statements that planned to practise deception on users. When doubts that fraud has occurred arise, we can name it alleged fraud. However, we have a verifiable instance of fraud only when a court case is proven.

As a subset of fraud Jones (2011), the essential kinds of financial report fraud exist;

First, financial report fraud when a company utilises accounting does without the permission of regulatory frameworks, hence fraud in a law court.

The second type of fraud that is major is the cases when transactions invented. Therefore, unexisting businesses recorded in the form of fictitious sales or fictitious inventory. Fraud is material-based.

The survey's respondents reported the average financial report fraud over the U.S. $3.6 billion (ACFE, 2020), with the average loss per case $ 1.509.000. It is a global survey that ACFE (2020) carry out. This research analysed 2504 cases from 125 countries. More specifically, in Western Europe (include Greece) appeared 128 cases which are 7% of the whole sample. Also, in the same research with the most cases of fraud occurred in the United States and Canada with 895 cases (46% of the entire sample. Then Sub – Saharan (301 cases-15%) followed Asia Pacific (198 cases -10%). Furthermore, the Middle East and North Africa are the same as Western Europe, with 127 cases (7%). Finally, Central Asia, Eastern Europe, Southern Asia, and the Caribbean appeared at 5%.

According to the same survey in Western Europe, including Greece, the most common occupational fraud schemes are corruption, billing, non-cash, expense refunds, cash on hand, financial statement fraud, check and payment tampering, and cash theft skimming, payroll and register disbursements.

In Western Europe, occupational fraud mainly detected by internal audit and management review. In Western Europe, the most public anti-fraud controls are the management certification of financial statements, code of conduct, external audit of financial statements, internal audit department, management review, independent audit committee, anti-fraud policy, and fraud training for managers, executives and employees. The median loss for fraud cases in Western Europe was $ 139000. Of 128 fraud cases in Western Europe, 21 was in Greece.

According to the Fraud Tree (figure 1), the three occupational fraud classes are; corruption, asset misappropriation, and fraudulent financial report, each with subcategories.

The three core types of fraud tree are fraudulent financial statements, asset misappropriation and corruption created by the perpetrator. Perpetrator caused misstatement and omission intentionally. The fraudulent financial information appeared in 10% of cases. Asset misappropriation happened by employee stealing, and it is the most common cause. Asset misappropriation occurred in 86% of cases. Asset misappropriation is the most public and the least expensive. Fraudulent Financial statement is the least public but the most costly. Corruption was the most public scheme in the worldwide region.

In the same survey ACFE, (2020) the more significant risk which present by asset misappropriation are: non-cash, billing, skimming, expense reimbursements, cash on hands, check and payment payroll, tampering, register disbursements, and cash larceny.

This thesis analyses the fraudulent financial statement as one of the most expensive occupational fraud schemes. Also, the most recent fraud scandals in Greece are Folie-folie, National insurance and MLS. All these cases have insufficient external audit control. So the topic of financial statement fraud and how well auditors approve financial statements come on media.

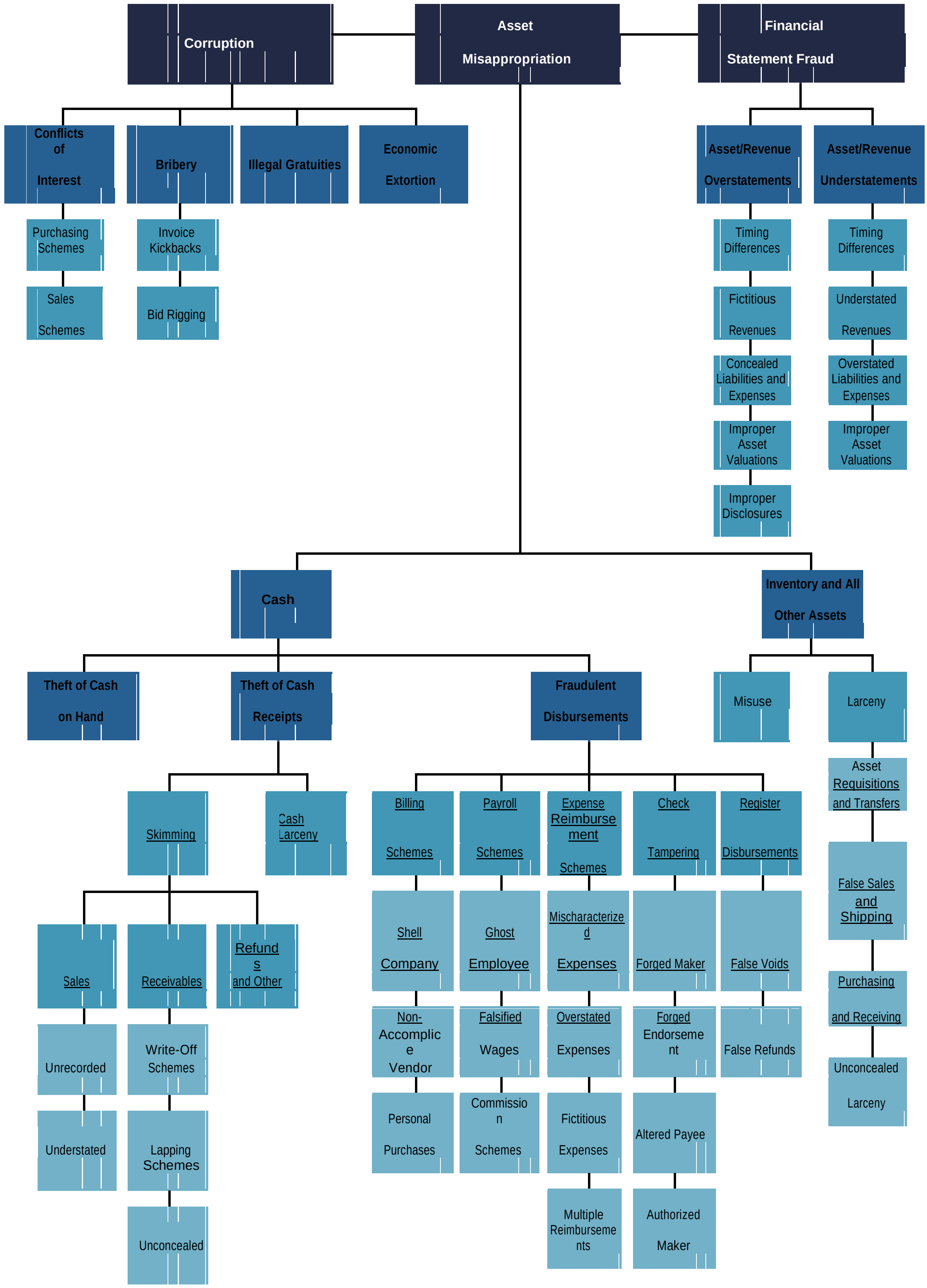

Figure 1:Fraud tree. Source: Wells (2005)

3.3 Classical Theories on the Determinants of Financial Statement Fraud

3.3.1 Fraud triangle theory

The three elements of FFS summarised in Figure 2 (Cressey, 1952). In the last few years, Donald R. Cressey's hypothesis (1919–1987), which tries to elucidate the conditions that generally occur when a fraudulent activity takes place, has come to be popularly referred to fraud triangle (Figure 2), which represent the perceived pressure, opportunity and rationalisation respectively. The element at the top of the diagram relates to an individual's motive or pressure to engage in the fraudulent act. In contrast, the two factors present at the bottom of the triangle comprise supposed opportunity and rationalisation (Wells, 2011, as cited in Rasha &Andrew, 2012). As shown in Figure 2, the two factors interact with one another in the triangle of fraud.

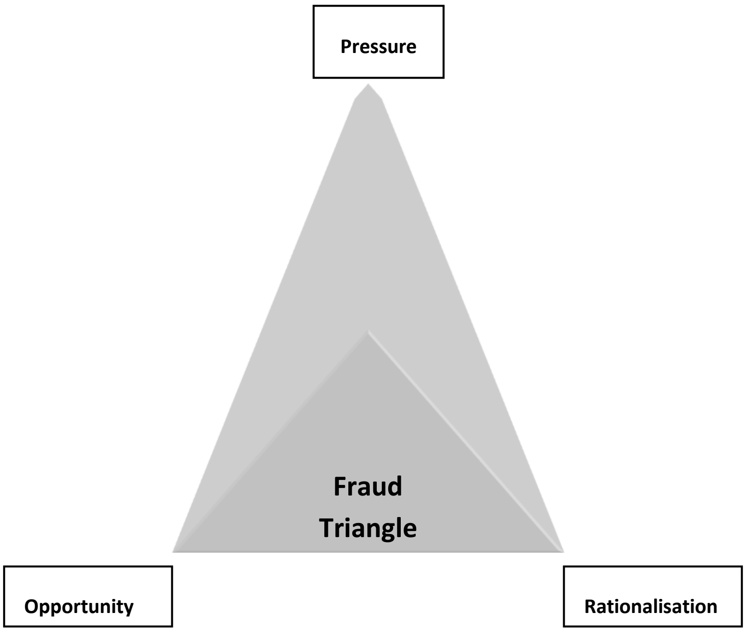

Figure 2: Fraud triangle

Rezaee (2002, pp 70–72) used a "3Cs" model comprising conditions, corporate structure and choices to explain incentives, opportunities and rationalisations for FFS. To illustrate the conditions he suggested FFS will take place if and when the profits to the person who commits the fraud offset the associated costs estimated using possibility and the effects of detection and, from this point of view, financial statement fraud will take place mainly in conditions of economic pressure that results from an ongoing worsening of earnings, a recession in organisational operation, a non-stop turn down in industry function or a general financial downturn.

In terms of opportunity, he considers the following "because financial statement fraud typically committed by the top management team level rather than lower management or employees, one would expect incidences to occur most often in an environment characterised by irresponsible and ineffective corporate governance. Management would be more reluctant to engage in financial statement fraud when an effective corporate governance mechanism increases the probability of prevention and detection".

The model demonstrates that when environmental pressure and corporate structure do not have a severe effect, the choice respected. Financial report fraud enhanced by cautions prompted by hostility, ethical code deficit or ill-advised inventiveness or originality by management.

3.3.2 GONE theory

The GONE theory is a method that classifies risk factors of fraud and designed by four letters: ‘G’for greed, ‘O’for opportunity, ‘N’for need and ‘E’for exposure (Bologna et al., 1993). The GONE theory primarily applied in studying asset misappropriation; however, the four risk factors are also applicable in interpreting fraudulent financial statement, as indicated in Figure 3.

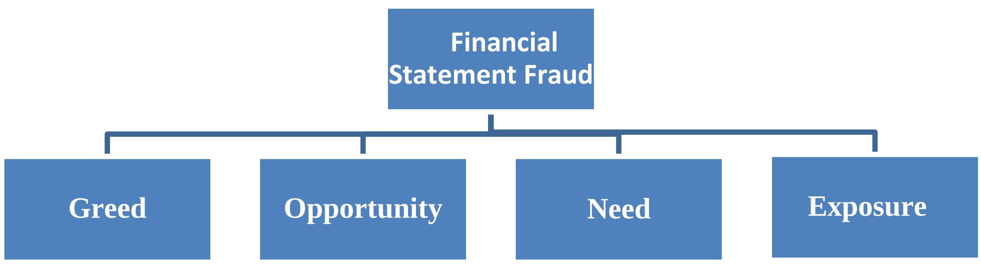

Figure 3: GONE theory

The main party in financial statement fraud is corporate management, whose ‘greed’ directed towards receiving high dividends or compensation or having opportunities to gain rationed shares and additional shares, thereby indirectly achieving personal economic benefits. This greed transforms into a “need’ for a fraudulent financial statement. Based on the advantages of daily management activities and internal information, corporate management has the ‘opportunity’ to produce fraudulent financial reports. ‘Exposure’ depends on the possibility of financial fraud disclosed by external auditors and regulators.

3.3.3 Risk factors of corporate governance

Jennings et al. (2006) and Duncan (2009) emphasised that corporate governance as the most significant cause that affects financial report fraud. Corporate governance is answerable for developing and overseeing the ongoing mechanisms in a company. Corporate governance is also responsible for eliminating financial report fraud foundations through palliating effects of incentive, prospect, and rationalisation, as a multi-faceted concept that includes narrow and broad definitions, a narrow definition of corporate governance provided by Williamson (1975). Williamson (1975) emphasised the need for setting up a governance structure, which includes general meetings of stockholders, executives, regulatory boards and top management to govern corporations. Also, Jensen and Meckling (1976) stated that corporate governance should emphasise the link between owners and managers of companies to make their benefits consistent. Fama and Jensen (1983) observed that corporate governance should resolve the primary agent challenge caused by the separation of management and ownership to reduce agency cost.

A broad definition of corporate governance was put forward by Brenner and Cochran (1990), which incorporates stakeholder theory: the idea that corporate governance should bear the shareholders’ interest in mind, including that of stockholders, creditors, suppliers, employees, the government and the society. Moreover, Qian (1995) argued corporate governance is a structure of arrangement used to manage the relationship among investors, the management and employees. Finally, Li (2001) argued that broad corporate governance is a system that includes formal and informal internal and external governance and comprises a relationship to balance the benefits between the companies and their related parties.

3.3.4 Principal-agent theory

An agency relationship formed when one or more persons employs another authority to the agent encompasses a contract between owner and manager (Jensen and Meckling, 1976). While the agent is held accountable for the owners' benefits, the managers also have interests in exploiting their welfare (Ujiyanto and Pramuka, 2007). Therefore, a conflict of interest often occurs between the owner and agent, affecting the quality of reported earnings. Asymmetric sharing of information with the owner as a means of earnings management is financial report fraud, which agrees with Rezaee (2002) findings, who stated that earnings management are closely associated with financial report fraud. Therefore, unnoticed by the owner, they may develop into FFS that are misleading. Hence, misleading and detrimental as it is, agency challenges associated with owner and agent can lead to financial report fraud.

According to Chiraz (2020), principal-agent theory replies to the next questions: What is the agency problem? What are the agency problem's underlying concepts, and how they are related with the fraudulent financial statement? What are the elements of agency costs?

Agent theory studied in accounting in detail by Hdofor et al. (2015). They explain that agency theory based on two hypotheses. The first hypothesis is the information asymmetry that exists between principals and agents. The second hypothesis is that principals and agents have different interests. Principals expect managers to succeed in the company in the most significant part of the owners. Managers take further incredible info about the company's operation, and as there are different conflicts, managers may work against owners. Self-interested and unethical managers can use fraudulent actions to growth their fortune.

One of the biggest challenges of a firm is to reduce information asymmetry to agents. Shareholders have misleading information on how managers operate. So as misleading information exists between managers and shareholders, information asymmetry labelled as "lack of transparency", and it is an opportunity for managers to manipulate financial statements (Ndofor et al.,2015). Furthermore, principals try to investigate more information by the auditor's report for the action of owners.

This information asymmetry is known as a moral hazard. Barosso et al. (2018) support that moral hazard gives the shareholders incentives to commit fraud that may be undetected due to financial statements' falsification.

The most characteristic example of information asymmetry is the Enron scandal. In this scandal, the audit report was "clean" despite misleading information in the financial statements. So the audit company ignores users for the real data. So the shareholders of Enron's were unable to know what exactly happens in the published financial statements.

In this thesis, we try to extent agent theory in the financial statements of Greece. This research associate agent theory with financial statement fraud. As we analyse in the next chapter, we include the auditor's opinion as a qualification criterion to characterise firms as fraud or non-fraud.

3.3.5 Relation of accounting theories and financial accounting fraud

Financial statements appear to the firm's financial position and provide financial information to shareholders, regulators, banks, and other users. The information provided by financial statements should be accurate and fairly, but some factors intentionally manipulate the financial statements and lead to fraud. So all the above theories try to explain the aspects in which firms falsify their financial statements. This research attempts to determine and associate these factors with financial accounting fraud.

According to Yesiariani and Rahayu's (2017) research, which investigates financial statement fraud, external pressure and rationalisation are significant variables to financial statement fraud. Furthermore, their study has proven that financial stability, change in auditor, nature of the industry, financial targets, and personal financial needs are significant factors for financial statement fraud. Also, these factors analysed with the Fraud triangle theory and GONE theory.

Furthermore, another research Zaki (2017) apply different models like and M-score by Beneish and Z-score of Altman of FFS. They found that the theory of the Fraud Triangle explains the factors of FFS.

Another research of Annisya (2016) support that financial stability calculated by the ratio of changing in total assets is a significant FFS factor. The same study observes the following ratios as substantial variables for financial statement fraud. They look at leverage ratio, which measures the external pressure, return on assets that measure the financial targets, and the nature of industry measured by the change in inventory and auditors opinion. Also, all these factors examined in this research.

Research of Miftah and Murwaningsari (2018), Handoko and Ramadhani (2017) try to explain good corporate governance theory on fraudulent financial statements. In their study described that financial statement fraud committed by an independent board of commissioners. They conclude that the size company and the auditor firm's size are extrinsic factors of fraudulent financial statement. In contrast, the economic practice of the audit committee, which positively contributes to fraudulent financial statements.

In the study of Hexana (2020), efficient corporate governance is the smooth communication among auditors (external and internal), directors and the board of commissioners. They define corporate governance as the system in which there are responsibilities and business distribution rights among different participants.

Last but not least is agency theory. This thesis also uses agency theory to explain the fraudulent financial statement. The goal of this theory is to associate with corporate accounting scandals.

3.4 Accounting Scandals

3.4.1 Profile of creative accounting in Greece

In light of the classical theories of financial report fraud determinants, Greece and many other countries have suffered due to many accounting scandals. As a consequence of such economic scandals, many firms have gone bankrupt. The history of Greek accounting scandals started when Greece joined the EU in 1981. Greece, in the last two decades, has accounted for the most accounting and fraud scandals. EU membership ensures lower limit control with unlawful importation of products such as cigarettes, food, alcohol and petrol (Kourakis, 2001). These cases involved a financial company (ETBA Bank), an accounting software company (Ipirotiki Software & Publications SA), an underwear clothing company (Sex Form SA), a health club chain (Dynamic Life) and Bank of Crete related scandal; the Capital Market Commission has already reached a verdict. Spathis (2002,p. 179) stated the following: "in Greece, the issue of false financial statements has lately been brought more into the limelight in connection primarily with a) the increase in the number of companies listed on the Athens Stock

Exchange and b) the raising of capital through public offering and attempts to reduce the level of taxation on profits".

3.4.2 Profile of creative accounting in international scandals

The Austrian economist Joseph Schumpeter argued that economic activity occurs in the following four stages: expansion, crisis, recession and recovery. According to Schumpeter, the background of the problem may continue for two to eleven years. When we say that the economy is at a stage of the crisis, the public and private investments reduced, which implies a dramatic increase in unemployment, decline in purchasing power, drop in the market value of many businesses and an increase in mergers acquisitions. The level of public and private investments mainly influences the macroeconomic data.

The recent global financial crisis began in the U.S. banks that issued subordinated loans. These loans impacted large economic groups and created risks that reduced the confidence of both investors and depositors. Furthermore, this crisis affected the profitability and the liquidity of many companies, leading many to bankruptcy. Several of these companies used legal or illegal accounting methods to smooth their earnings to survive. The result comprised a falsification of their financial statements by using creative or fraudulent accounting.

Although it is an old fact, the quantity of corporate earnings restatement connected to accounting fraud, accounting abnormalities or violent accounting methods has dramatically augmented during the last few years. Furthermore, analysts, investors and regulators have paid much attention to it.

In the last few years, the amount of corporate earnings recurrences associated with accounting fraud, irregularities or practices has significantly increased and has drawn more attention from investors, analysts and managers.

Arthur Levitt advocated improving the quality of earnings reported in 1999 that powerful earnings management concealed the necessary firm's performance. The government increased strict interventions and regulations after the occurrence of numerous notorious accounting frauds and scandals. To ensure precision and consistency of corporate financial reporting, U.S. Congress in 2002 enacted the Sarbanes-Oxley Act. Although most of these scandals varied form those observed in the U.S., financial scandals also experienced in Europe, with the most notorious being the Parmalat scandal during the same period. The two characteristics of frauds; High leverage and management fraud, were more common in many of the cases investigated in Europe over the past 25 years.

While accounting issues show significance in many Europe business disasters, which is significantly less than that in the U.S. following increased accounting fraud (e.g. Enron, WorldCom and Adelphia), Levitt has stated: sounds prophetic. Significant government interference and regulations came after these cases of fraud. U.S. Congress in 2002 enacted the Sarbanes-Oxley Act to facilitate the precision & consistency of business economic reporting and leaks. Several financial scandals also took place in Europe at that same time (e.g. the Parmalat, which was the most infamous of all). However, varied the majority of them in a great deal from the ones in the U.S. In trying to find out the causes that show significance led to Europe's most significant business breakdowns in the last 25 years, researchers found out that excessive control and fraud in the administration were the two features standard in many of these incidents that had examined. Nevertheless, the writers concluded that even though discovered accounting matters to be vital in many business failures in their research, the number was less significant than the great U.S. business breakdowns.

There are many accounting scandals in Germany, Italy, Spain, U.S., U.K., Netherlands, Sweden, Greece, Australia, China, Japan and India. Most of these accounting scandals presented in the study conducted by Jones (2011). In most of these cases, these accounting scandals led to more comprehensive corporate failure outcomes.

3.4.3 Overview of accounting scandals

The following table contained some of the most significant scandals in the world.

Table 3: Accounting Scandals

Year	Firm	Country	Accounting Issues
2000	Lavreotiki	Greece	Insider trading and share manipulation
2001	Enron.	USA	Off-balance sheet financing; loans as operating cash flow
2001-2006	Sanyo Electric	Japan	Impairment loss of subsidiaries' shares on its parent-only financial statements not recorded properly; paid illegal dividends
2002	WorldCom	USA	Acquisition reserves; excessive cost capitalisation
2003	Parmalat	Italy	Fraudulent accounting; falsification of earnings, assets and debts
2004	Sex Form AE.	Greece	€5 million misappropriation that led to the closure of the company
2004-2005	Ipirotiki Software	Greece	A manipulation scheme that artificially influenced the price and marketability of the company's shares
2004-2007	Dynamic Life	Greece	Falsified financial statements; hiding a loss of €6 million
2005	Zapf Creation	Germany	Reclassification of expense items; unrecognised provisions (for example for bonus payments, returns); failure to allocate marketing and sales expenses to proper period; restatements resulting from barter transactions.
2006	Skandia	Sweden	Questionable apartment renovations and remuneration programme; embedded value insurance accounting
2008	Lehman Brothers	USA	Overleveraging; underestimate of risk associated with holdings of collateralised assets
2011	Orascom Hotels and Development	Egypt	The parent company of Orascom alleged to have misrepresented its ownership stake in the hotel group as it detected discrepancies between the company's financial disclosures and the shareholders' register. Moreover, the chairman of the board accused of providing misleading financial statements and manipulating stock prices. Ultimately, the firm settled with the Egyptian Financial Supervisory Authority, the country's financial regulator, to avoid prosecution.

2012	Kinross Gold	Canada	The company acquired 100% of the shares of a gold mine in Mauritania, Africa, and in its 2010 annual report proposed aggressive expansion plans. The expansion plan was never implemented in that form. Thus, class action lawsuits were brought against the company accusing it of overstating assets (i.e., not having disclosed a write-down of the goodwill from the acquisition) and withholding material information about the lower than expected gold quality at the acquired site as well as the stalling progress of the expansion project
2013	LVMH	France	The French stock market authority AMF sanctioned the company to pay a penalty of EUR 8 million for misinforming investors. LVMH did not properly disclose an equity stake in one of its rival companies, Hermès, that it had amassed over time.
2013	Stora Enso Oy	Filand	The large forestry products and paper manufacturer was accused of accounting manipulation and wrongful dividend payments to cover losses from the sale of one of its group companies. The incident led to follow up investigations by the Finnish Financial Supervisory Authority, but no further actions were taken.
2015	FC Barcelona	Spain	The football club playing in the Spanish premier league (La Liga) was accused of engaging in complicated tax evasion schemes around the signing of the Brazilian star forward Neymar. Payments were disguised in order to avoid reporting and tax requirements.
2018	Carillion	UK	Work found to be unacceptable according to UK watchdog in June 2018

As we can conclude, the phenomenon of falsification in financial statements is worldwide. All the countries have firms that use the techniques of creative accounting to falsify their financial statements.

According to Mohammad Annes (2020), there are “red flags” warming for all users, indicating potential problems in published financial statements. The question is how we can identify these “red flags”. The answer to this question is that there is no universal standard for identifying these “red flags”. Identifying these “red flags” depends on the research methodology of an analyst, investor, and economist employs. This includes that analyst, investor and economist employs the need to study historical data, examine financial statements, and receive economic indicators. There are different levels of “red flag” such as are economical, corporate, industry and “red flags” in financial statements.

Specifically, the most common techniques which should analyse users are:

- Capitalisation analysis of the firm
- Examine historical data of EBIT, ROE, ROI, operating expenses, revenues.
- Analyse and compare the industrial position
- Examine the ratios of Price to sales (P/S) and Price-earnings (P/E)
- Examine the structure of corporate governance.
- Analyse the consolidate financial statements
- Examine the stock price trend
- Examine inventories
- Examine related risk factors for firm and industry
- Examine the expectations of stakeholders.

Furthermore, some essential red flags may cause suspicion for the firm’s financial position. These are:

- Too good to be true. When the results of published financial statements are over attractive, it needs in-depth investigation to see if these results are for a long or short period.
- Should examine the comments of the audit report. The audit report should indicate observations for serious doubt and misstatements in the reported financial statements affected by managers.
- Accounting policy. Users have to examine Earnings before Interest Tax Depreciation and Amortization (EBITDA) and Net Profit before tax (EBT) as unusual accounting policies reflect these ratios. Unique accounting policies

may include overestimation of assets, underestimation of assets with the use of depreciation. One more technique is the change method in inventory valuation. Furthermore, it creates reserves, different valuation processes in the account of research and development expenses and the manipulation of profits through non-operating activities.

- Changes in accounts and management frequently. Users should examine the ratios of debt to equity and working capital turnover to signal worsening operation conditions. Change in CEO or Senior Management may indicate different firm policies.
- Transactions complexity. Transactions with third parties that can not understand well. For example, the Enron scandal used affiliated companies to transfer liabilities from their accounts.
- Bonus and performance. When managers have the incentive of a bonus, there are more possibilities to manipulate financial statements.
- Changes in gross profit margin. We are increasing Gross profit sometimes in a not good sign. Gross profit should be related to the level of sales and expenses.
- Debt ratios. Users have to investigate debt ratios as large debt can lead to bankruptcy in the future.
- Finally, changes in inventory and debt which associate with sales. These accounts have to be examined to sign that future stock write-downs follow or impede bad Debts.

In concluding, detection with “red flags” maybe is a manner that can detect the manipulation in financial statements easily for shareholders, banks, regulators, investors and other users.

3.5 Components of Financial Statement Fraud

3.5.1 Parties related to creative accounting

Many parties are interested in the subject of financial statement fraud. These parties comprise managers, shareholders, auditors, merchant banks, e.t.c. These parties have an essential role in fraud and creative accounting. The legal authorities are interested when creative accounting turns into fraud. The corporate environment and the firm's economic conditions play a vital role in fraud associated with creative accounting. For example, Crutchley, Jensen and Marshall (2007) found rapid growth, high earnings, a reduced outsider in the audit committee & outsider director smoothing can lead to an accounting scandal. Also, the economic conditions and the personal ambitions of the managers are critical contributory aspects of FFS. Accounting flexibility permits managers utilisation of creative accounting. Jones (2011) described exactly how creative accounting operates in an economic environment: Although complying with the law and transgressing its spirit, the idea for using creative accounting by managers may be from merchant banks. Regulators seek to regulate and limit creative accounting by setting regulations and rules. Using supervisory structure as a reference point, auditors drive to ensure accurate and fair accounts. While managers are the causes, shareholders experienced the consequences of creative accounting. Share analysts seek to adjust the accounts for creative accounting by efficiently pricing stock. Shareholders are significant losses if the firm goes bankrupt. Creative accounting has also caused bankers and creditors to worry because it conceals poor results.

Thus, to minimise fraud from creative accounting, efficient internal control, good corporate governance, and independent audit committee creation are required.

3.5.2 Managers

In theory, managers carry out the administration of the firms that shareholders own. Thus, it should be the interest of managers to satisfy shareholders. However, in reality, managerial self-interest may dictate the accounting system's flexibility to carry out fraud and creative accounting. Managers could use fraud and creative accounting either to raise or reduce profit or liability. Their motivations vary. For instance, a manager's salary may be dependent on an increase in profit. Also, if managers want to meet profit, they can manipulate profits by using creative accounting and fraud. One more reason for the managers to use the accounting techniques to manage accounts is to avail a bank loan.

Generally, it is difficult for outsiders to detect creative accounting and fraud. Jones (2011) included an instance that explains in detail the manipulation in accounts as follows: "A company is operating a fleet of lorries, and each lorry will do 100 000 miles in its working life. Currently, each lorry's estimated annual mileage is 20 000 miles. Each lorry costs £50 000 and, therefore, £10 000 is written off each lorry each year in depreciation. If the managers think that the lorry will do 10 000 miles next year, depreciation will fall to £5000 per year. Profit will increase by £5000. This is true and fair and reflects economic reality. It is not creative accounting. However, managers may pressure managers to interpret the number of miles the Lorries will do generously to reduce profit. So, this is creative accounting".In this example, outsiders can't know the truth.

3.5.3 Investment analysts

Investment analysts investigate the accounts of firms to suggest to investors whether stocks and shares are priced efficiently. Thus, investment analysts should have the ability to detect creative accounting. The literature includes some examples in which the investment analysts failed to perceive fraud and creative accounting. For instance:

“Gwilliam and Russell (1991) showed that in 1989 analysts failed to spot that overstated Polly Peck’s earnings or that the company was losing huge amounts on its overseas borrowings. Indeed, only days before one of the most spectacular collapses in British corporate history, analysts predicted a substantial increase in profits. In another example, Breton and Taffler (2001) presented analysts with a set of doctored accounts. They used nine creative accounting techniques across different accounting areas, for example, deferred taxation, pensions, off-balance-sheet financing and hidden interest charges. Very few analysts adjusted, or even detected, any of the creative accounting practices that used”.

In general, investment experts must be autonomous observers of the firms. However, in real-time, this is not the case. The main reason is that investment analysts work for merchant banks that have the firms as their clients, making it difficult for them to accuse their clients.

3.5.4 Regulators.

Regulators control creative accounting and fraud by designing counting rules and regulations that ensure flexibility for the fair and accurate view not to demean the currency of accounting. With the national and international regulatory frameworks developed over the years, new rules and regulations are introduced to cob accounting scandals.

Regulators work against creative accounting. In most countries, accounting regulations often comprise companies’ acts, government regulations, accounting standards and SEC regulations, while the IASB sets the international accounting standards (IAS) at the international level. Therefore, to allow for the expression of a fair and accurate view, the financial report’s essential principles should conform to the economy. The observed main difficulty for regulators is that flexibility in delivering a fair and accurate view is the same features employed by creative accountants.

3.5.5 Auditors

Watts and Zimmerman (1990) argued that inspecting financial reports helps reduce irregularity in the sharing of information and protects shareholders' interests by facilitating rational assurance that the financial statement is devoid of misstatement. Nevertheless, in reality, management fraud detection is challenging using standard audit procedures due to the shortage of knowledge associated with management fraud's features and lack of experience by most auditors required to detect it. At the same time, managers at one end deliberately try to deceive examiners.

Fraud and creative accounting are significant challenges for auditors when checking accounts presentation for a fair result. One challenging issue is the dependence of auditors on their clients. This situation is complicated, as most audit firms are private. Thus, they are concerned with their reputation and their profits. Auditors fear both creative accounting and fraud, both of which are difficult to detect. Auditors have a great responsibility towards what they can determine about the state of the financial statements. Jones (2011) included some examples in which the auditors could not see that the results were manipulated as follows: A British auditor (Stoy Hayward) was asked to pay a £75,000 fine and £25,000 in cost when Poly Peck collapse (Perry, 2002).In extreme conditions, the failure of the firm being audited can occur. Arthur Andersen experienced similar in the USA when one of the auditors was destroying implicating evidence. In 2006, ChuoAoyama Pricewaterhouse Coopers, a Japanese auditing company, cause 2000 Japanese company's auditing to be stopped as negligence was observed in auditing Kanebo.

3.5.6 Shareholders

External shareholders are probably the victims of creative accounting and fraud. Shareholders cannot trust anybody, as nobody protects them. Suppose managers manipulate the accounts, and the investment analysts and the auditors do not detect the manipulation. In that case, a shareholder can lose their investments or engage in investing in a sub-optimal way.

Jones (2011) included some cases, such as those observed in Enron, City of Glasgow Bank, in which the shareholders lost their money. These lead investors to go bankrupt, which was also contributed by a lack of information by outside shareholders on the company's state.

3.5.7 Merchant banks

The role of merchant banks is complicated. Several times managers and accountants ask merchant banks to consult them about creative accounting and fraud. What follows is a typical example of the role of merchant banks: as far as the Enron scandal is concerned, for instance, there has been a lot of thought on the part of banks in settling complex deals to establish balance sheet financing systems Merchant banks perform complex roles amidst providing advice on creative accounting and fraud to managers and accountants. Using the Enron scandal as a case study, questions concerning bank involvement in making complex deals to balance their sheet were raised, especially strong in the U.S senate. The U.S. Senate Permanent Subcommittee on Investigations provided 'document showing banks and foreign firms syphoned billions of dollars setting up and running secrete offshore shell companies (Iwata, 2002).

In return for consideration for many other transactions, these financial institutions which were aware of Enron questionable accounting actively aided Enron. However, in their defence, the bank's representatives stated that their accounting transactions were entirely appropriate as they had followed GAAP but deceived by Enron. In effect, corporate advisors compromised ethics for fees and other business considerations. More so, merchant bankers are significant beneficiaries of creative accounting, as they can plan and market innovative accounting schemes.

3.5.8 Other users

Other users are bankers, suppliers, employees and other stakeholders, such as trade unions and the government tax authorities. These users depend on a firm's economic performance. Bankers prefer consulting a healthy balance sheet to judge whether they should give a loan to a firm or not. Therefore, the suppliers want to know repaid these loans, and the employees require job security.

3.6 Reasons: Motivations for Creative Accounting

3.6.1 Manipulation practices

Stolowy and Breton (2003) attempted to identify a hypothetical structure for the accounting manipulations as follows: "The fundamental principle which their theoretical framework is based on is the following: the aim of publishing financial information is to reduce the costs of the enterprise projects financing. But this reduction depends on the risks to transfer the riches as the agents perceive them on the market. The practical means to operate these transfers are based on the results and the balance between the debts and share capital".

Changes in the two ratios are the purpose of accounting data management. Deviation of per-share result (first ratio) and connection between the assets and liabilities (second ratio). The first ratio could be altered by subtracting or adding some specific expenses or result profits used as a computational base for per-share results. The second ratio could be altered by raising benefits or concealing some financial deals from the balance sheet.

3.6.2 Methods: Opportunities for creative accounting

Jones (2011) stated that fraud and creative accounting result from account flexibility that allows accounting policies to be altered to change the reported accounting figures.

There are four main financial reports companies is obligated to file: the account of profit and loss, the economic situation of a firm, report of equity change and report of cash flow, which can be used for fraud and creative accounting.

The purpose of an income report is to inflate profit by increasing income and reducing expenses, and vice versa. The purpose of a balance sheet report is to increase a firm's net income, while a cash flow report aims to increase functional cash flow to the detriment of other cashflows.

The boundary between fraus and creative accounting is unclear.

Also, Jones (2011) stated that the first two approaches' purpose increases the income report's profit via increasing sales or decreasing expenses. The third and fourth approach boosts assets and reducing liability. The fifth approach aims to increase the flow of money by increasing the functional flow of cash.

3.6.3 Why does financial statement fraud occurs? Motivations for creative accounting

In a perfect world where enterprises have maximum profit, minimum expenses, high share prices and high bonuses, there is no creative accounting motivation. However, in the real world, there are many motivations for fraud and creative accounting. In general, primary fraud and innovative accounting methods are maximising reported sales and reported profits, increasing net assets, and decreasing the liabilities that are not necessarily simultaneously. The levelling of income effects is prominent due to the increased level of requirements in countries with highly conservative accounting systems (Amat et al., 2003). A firm making a loss will minimise its reported loss in the current year for subsequent years to appear better, a phenomenon called "big bath" accounting.

Jones (2011) stated that the incentives for fraud are the same as that for creative accounting. The difference between fraud and creative accounting is that the enticements for copy are greed, gambling and lifestyle. Studies such as those conducted by DeAngelo (1988), Healy and Whalen (1999), Beneish (2001) and Brennan & McGrath (2007) and many others analyse the incentives for fraud and creative accounting and summarise the following factors as being significant motivations:

- **To meet internal targets or personal incentives to** meet senior executives' targets regarding share prices, sales and profits, managers dishonestly want to alter figures or facts, thus protecting and increasing their salaries, job security and personal satisfaction from which they benefit directly. New U.S. bank managers show off their proficiency by emphasising the previous managers' poor management (Dahi (1996).
- **To meet external expectations or market incentives.**The motivations for this include three categories; First, the company meeting different expectations from its stakeholders; and for personal interests, employees and customers requires a firm long term survival while suppliers require guarantee respecting long term connection with the company and payment. Second, to impress shareholders to retain stable stock prices, enterprises want to provide income smoothing. This approach favour remedial features against short term mean of assessing an investment on instant yields. It also avoids the increase in the expectations to be met by the management. Third, society expects managers to use creative accounting, as everybody is using creative accounting. Thus, managers may feel that it is legitimate for them to do the same. The market expects managers to manipulate figures by recording outrageously increased earnings rather than increasing earning following increase firm worth (Watts and Zimmerman, 1986). Thus, following this argument, society develops the idea of creative accounting.

- **Special circumstances**.

This category has many different motivations, including gearing and borrowing, taxation and an initial public offering (IPO).

This category has many different motivations, including gearing and borrowing, taxation and an initial public offering (IPO).

An IPO window dressing or a loan is necessary as it can do it before corporate events. A firm's tendency to be near violation of debt agreements prompts them to formulate income-increasing changes in its accounting policies (Sweeney, 1994). Also, with many loans made available by firms, it is difficult for them to borrow more and more as debt providers are concerned with their funds recovering. Thus, a firm faces a penalty if it does not abide by the debt covenants. This encourages the use of balance-sheet-based financial techniques to remove selected debt from the balance sheet not to breach any loan covenants. Also, creative accounting could boost shares by decreasing the apparent level or borrowing with a good profit trend appearance.

The desire for tax benefits can cause creative accounting and fraud (Niskanen and Keloharju, 2000; Herrmann and Inoue, 1996).

Another motivation for creative accounting and fraud exists when firms decide to enter the stock market. Stock markets have rules for firms that wish to register. Thus, this may provoke firms to use creative accounting to maximise the reported sales and profits or enable them to issue an ideal number of shares. We summarise the most important benefits for firms using creative accounting and fraud, as demonstrated in Table 4 given below.

Table 4: Rewards for managing profits and financial position

Category	**Aims that firms are trying to succeed**
Share-price effect	Higher share price Reduce share price volatility Increase firm value Lower cost of equity capital Increased value of stock options
Borrowing cost effects	Improve credit rating Lower borrowing costs Relaxed or less stringent financial covenants
Management performance evaluation effects	Increased bonuses based on profits/ share price
Political cost effects	Decreased regulations Avoidance of higher taxes
Source: Mulford and Comiskey, 2002	

3.7 Conclusion

Chapter three has showed a broad literature review of the prior research conducted on fraud, creative accounting and financial report fraud. We concluded that despite extensive research that has been shown in this field, the most critical gap in the literature focuses on new ideas to interpret the incidence of FFS. This chapter considered the causes of FFS from subjective, objective and conditional aspects. Regarding the personal element, we argued that senior management's bounded rationality creates personal motivations, limited perception and knowledge, and an environment, resulting in them committing financial fraud. Accounting information, as the objective cause of financial statement fraud, has economic characteristics. It provides no direct utility to the production of a firm.

In contrast, its value only increases through its ability to influence related parties' decision making concerning resource allocation. The positive and negative externalities of accounting information may affect the potential of whether financial statement fraud is undertaken or not. The empirical analysis is presented in the next chapter.

Chapter 4: Identification of fraudulent financial statements in Greece by applying machine learning techniques

4.1 Introduction

This chapter contains fifteen sections and tries to respond to the first three research questions. The early research question tried to find out which financial ratio is related to the detection of FFS. The second research question related to the capacity of financial ratios to predict FFS. The third research question strived to see whether computational intelligence techniques can be used to prevent and detect FFS. A large amount of firms accounts is used to estimate whether creative accounting and financial report fraud have occurred. Analytical review approaches are categorized into simple quantitative, advanced quantitative and non-quantitative techniques. Studies respecting certain corporate features of governance to the existence of FFS have been conducted. These have dealt with the management earnings literature. These researches relate the terms income smoothing, earnings management', or fraud', as these terms are broadly synonymous with creative accounting and fraudulent financial statement.

4.2 Predicting Financial Statement Fraud versus Predicting Financial Distress and Bankruptcy in Prior Research

An average of an 8% decrease in stock price occurs with suspicious accounting's announcement. Going bankrupt with 0.5% is as rare as catching a fraudster. Thus, fraud happens in companies with high growth potentials (e.g. software, internet or new technologies) that are cash-tasting.

Financial ratio models could detect fraud or severe misstatements like the bankruptcy of a company as they are relatively accurate in identifying fraud firms. However, a lot of suspicious firms have no fraud announcements subsequently upon investigation. Investors price are not protected as fraud firms have a concrete and encouraging price of previous stock performance. Raising stock price forms a basis for firms committing commit fraud.

What can an investor who holds stock do if the announcement of a suspicious accounting misstatement of a firm with a subsequent drop in stock price? Can ratio envisage fraud firm likely to survive? These questions are challenging to answer. Nevertheless, the fraudulent firm goes bankrupt with a few years (3 years) of a suspicious accounting misstatement pronouncement, suggesting that financial bankruptcy and suffering can be predicted by low accounting quality.

What are the essential financial ratios for predicting fraud and bankruptcy, and what are standard signals between the forecast of financial statement fraud and default? Studies propose fraudulent firms to have apparent sales growth, inventory and leases and in need of cash, which are good indicators for possible misstatements. Therefore, the fraudulent firm possesses an increased market presence, unlike the bankruptcy models in which the stock returns are harmful, and the ratio of market to book is low or insignificant. For the creation of fraud detection models, the models of Beaver (2005), Ohlson (1980), and Altman (1968) reports that financial distress is essential; as bankruptcy results in firms found to commit fraud, and firms filing for bankruptcy protection include a higher likelihood of being indicted for fraud due to the advanced enticement to participate in fraud in these financially troubled firms (Johnson, 2008).

Table five presents the previous literature in the prediction of a fraudulent financial statement from 1996 to 2013. This table shows the authors, the period of the sample which investigates, the number of non-fraud and fraud firms, the quantitative and qualitative variables which examined and the method which is used. We can conclude that variables should use no universally accepted to forecast the fraudulent financial statement. The most critical variables are associated with the ratios of sales, ROA, Working Capital, F-score, M-score, and corporate governance variables.

In our research, we investigate most of these variables. We investigate if these variables associated with the prediction of FFS. Furthermore, we investigate whether these variables can act as quickly factors in the prediction of FFS. We explain these attributes in detail in the section 4.10

Table 5:Predicting Financial Statement Fraud

Paper	Period	Sample		Accounting Variables	Other Variables	Classification
		Fraud	Non- Fraud			
Dechow, Sloan and Sweeney (1996)	1982-1992	92	85	**Accruals** **Accounting principles** **External financing**	**Board char.**[1] **Director char.** **Covenant default**	Not reported
Beasley (1996)	1980-1991	75	75	Growth in assets (+) Indicator for persistent loss (+)	**Board char.**[1] **Director char.**	15%
Beneish (1999)[2]	1982-1992	74	2332	**RECT/SALE growth (+)** **Gross margin growth (+)** **NCA/AT (+)** **Sales growth (-)** Dep growth (+) SGA growth (-) Debt/AT growth (-) **Accruals/AT (+)**		Pseudo R^2= 37% 58% correctly classified [3]
Erickson, Hanlon, and Maydew (2006)	1996-2003	50	100	Firms' desire for external financing (+) **Debt/AT (+)** BTM (-) P/E (+) ROA (-) **Sales growth (+)** Altman's Z (-)	CEO pay sensitivity (+) MV (+) Board char. Director char. Age of firm (-) M and A (+) **Stock volatility (+)**	Not reported
Dechow, Ge, Larson and Sloan (2011)	1982-2005	494.	132.967	**RSST accruals (+)** **ΔRECT (+)** **ΔINVT (+)** **% Soft assets (+)** **ΔCash sales (+)** **ΔROA (-)**	**Issuance (+)** Δemp (-) **ΔOplease (+)** **Ret (+)** **Lag_Ret (+)**	69% correctly classified [4]
Feng, Ge, Luo, and Shevlin (2011)	1982-2005	116	219	F-score variables	**CEO pay sensitivity (+)** CFO pay sensitivity **CEO paysclice (+)** **Director char.**	Not reported
Price, Sharp and Wood (2011)	1995-2008	444.	48376	WC accruals (+) M-score (+) **F-score (+)** Accruals quality (+) Disc. Acc. (+) **Residual audit fees (+)**	**Audit integrity's accounting and governance risk score(+)**	Pseudo R^2= 12%
Hribar, Kravit and Wilson (2013)	2000-2007	140	140	**Residual audit fees (+)** Accrual quality (-) **Abs_Disc acc. (-)** Smooth (-) Std. Dev. Of CFO (+) F-score variables	BTM (+)	Pseudo R^2= 11%

Notes:

1. Board char.: board of directors characteristics, Director char.: director characteristics.
2. M-Score=-4,840+0.920*DSRI+0.528*GMI+0.404*AQ+0.892*SGI+0.115*DEPI-0.172*SGAI-0.327*LVGI+4.697*TATA.
   F-Score=-7.893+0.790*rsst_acc+2.518*ch_rec+1.191*ch_inv+1.979*soft-assets+0.171*ch_cs-0.932*ch-roa+1.029*issue.
3. Based on the M-Score, the percentage of correctly classified manipulators ranges from 58% to 76%. The percentage of incorrectly classified non manipulators ranges from 7.6% to 17.5%.

The following table 6 listed the essential research conducted in the region of bankruptcy and financial distress prediction. These studies, mostly employee accounting variables, are ratios that indicate liquidity, profitability, capital structure. According to the previous literature results, we can conclude that these variables can predict bankruptcy with a high percentage.

Table 6: Predicting bankruptcy and Financial Distress

Paper	**Period**	**Sample**		**Accounting Variables**	**Market variables**	**Percentage Correctly Classified**
		Distress	No-Distress			
Classification Tests						
Beaver (1966)	1954-1964	79	79	CFO/TL (-) ROA (-) TL/TA (+) WC/TA (-) CA/CL (-)	N/A	1 Year - 97% 2 Years - 89% 3 Years - 89% 4 Years - 94% 5 Years - 91%
Multiple Discriminant Analysis						
Altman(1968)	1946-1965	33	33	WC/TA (+)[1] RE/TA (+) EBIT/TA (+) Sales/TA (+)	ME/TL (+)	1 Year - 94% 2 Years - 72%
Dambolena and Khoury (1980)	1969-1975	34	34	Profitability measures (5 ratios) Activity and turnover measures (4 ratios) Liquidity measures (4 ratios) Indebtedness measures (6 ratios) Standard deviation of each ratio		Not reported
Probit Models						
Zmijewski(1984)	1972-1978	81	1.600	ROA (-) TL/TA (+) CL/CA (+)		Approx. 40%
Logit Model						
Ohlson(1980)	1970-1976	105	2.058	ln (TA/GNP price-level index) (-) TL/TA (+) WC/TA (-) CL/TA (+) Neg equity (-) ROA (-) CFO/TL (-) Neg. ROA (2) (+) ΔROA (-)		1 Year - 95% 2 Years - 81%
Beaver, McNichols, and Rhie (2005)	1962-2002	544	74.823	ROA (-) TL/TA (+) EBITDA/TL (-)	Ln(ME) (-) LERET (-) LSIGMA (+)	1st decile 69% with accounting var. 1st decile 72% with market. var. 1st decile 80% with combined model
Campbell, Hilscher, and Szilagyi (2008)	1963-1998	797	1.282.853 [2]	ROA (-) TL/TA (+)	NI/MTA (-) [3] TL/MTA (+) CHE/MTA (-) RSize (-) LERET (-) MTB (+) Price (-)	Not Reported
Beaver, Correia, McNichols (2012)	1962-2002	1.251	134.113	Neg. ROA (-) ROA (-) Tl/TA (+) EBITDA/LA (-) Intersections with negative ROA	Ln(ME) (-) LERET (-) LSIGMA (+) Intersections with negative ROA	1st decile 56% with accounting var. 1st decile 50% with market var. 1st decile 64% with combined model
Hazard Rate Models						

Shumway (2001)	1962-1992	229	27.997	WC/TA (-) RE/TA (-) EBIT/TA (-) Sales/TA(+) ROA (-) TL/TA (-) CA/CL (-)	ME/TL (-) Rsize (-) LERET (-) LSIGMA (+)	1st decile 69% with Market var. 1st decile 75% with combined model
Chava and Jarrow (2004)	1962-1999	404	72.184	Shumway (2001)		1st decile 72% with market var. 1st decile 74.4% with combined model 1st decile 72.8% with IE4 1st decile 60% all firms[5]
Distance to Default Models						
Hillegeist, Keating, Cram, and Lundstedt (2004)	1980-2000	756	77.344 [6]	Distance-to-Default[7]		Not reported
Vassalou and Xing (2004)	1971-1999	93.702		Distance-to-Default[7]		Not reported
Multiple Models						
Bharath and Shumway (2008)	1980-2003	1.449	350.662	ROA (-)	Distance-to-Default [7] Ln(ME) (-) Ln(FD) (+)[8] LERET (-) 1/LSIGMA (-)	1st decile 65%[8] 1st decile 75.8%[8]
Correia, Richardson and Tuna (2012)	1980-2010	1.797	194.481	Distance-to-Default [7] Beaver et al. (2012) Bharath and Shumway (2008) Moody's EDF[10]		N/A[9]
Accounting Based Fundamental Analysis						
Piotroski (2000)[11]	1976-1996	14.043		F_ROA F_ ΔROA F_CFO F_ACCRUAL F_ΔMARGIN F_ΔTURN F_ΔLEVER F_ΔLIQUID EQ_OFFER		1.8% of high score firms (financially strong firms) gets performance related delistings while the percentage is 10.1% for low score firms (financially weak firms).

Notes:

1. Lower Z-Score indicates higher risk, and therefore the signs here are in line with other findings.
2. Monthly observations.
3. MTA is total assets adjusted: MTA = TA + 0.1(ME-BE).
4. Industry effects.
5. The sample includes all firms including financial institutions.
6. Different models have different number of observations. Numbers here are based on Shumway (2001).
7. Distance-to-Default is calculated as follows:
   $DD (t) = (\log (V_A/D))+(r - 1/2 * \sigma_A^2) (T-t) / (\sigma_A * \text{sqrt} (T-t))$, where V_A is value of the assets, σ_A is the volatility of the value of the assets, and D is the face value of debt. DD (t) is then transferred into a probability measure using the normal distribution.
8. Ln (ME) and Ln (FD) are the natural logarithms of market equity and face value of debt, respectively.
9. A probability measure based on a hazard rate model that includes only DD correctly estimates 65% of the bankruptcy cases in the first decile. A probability measure that includes DD and some other market variables accurately estimates 75.8% of the bankruptcy cases in the first decile.
10. They use the "power curve" to evaluate the various default forecast models. The differences across models seem to be small and not statistically significant.

4.3 Review of the related literature based on machine learning techniques

West (2015) supported that varying forms of financial fraud are present. Variegated methods of data mining are used in research to identify the best method for each type. The Federal Bureau of Investigation's data in their Financial Crimes Report of 2010 and 2011 in the USA found that they referred to the main types of financial fraud as Corporate Fraud, Bank Fraud, and Insurance fraud. Each type of these categories is divided into subcategories. Thus, corporate fraud divided into securities and commodities fraud and fraudulent financial statements. The second type comprises bank fraud divided into money laundering, mortgage and credit card fraud. Finally, insurance fraud is divided into automobile insurance fraud and health care fraud. In this study, as we have referenced in previous chapters, we would analyse financial statement fraud.

Data mining involves methods processing a huge amount of data to derive hidden meaning. West (2015) considered the following two types of data mining: computational and statistical. Bayesian theory and logistic regression are the statistical techniques that rely on conventional mathematical methods. In contrast, neural networks and SVMs are computational methods that are used in modern intelligence techniques. Furthermore, West (2015) believed that although these categories divide many similarities, the significant difference is the computational method's ability to adapt and learn from new problems compared with the statistical method that depicts rigidity. We study equally types of data mining. In particular, we evaluate the performance of various data mining methods plus the decision tree, Naive Bayes, Logit Regression, Random Forest, K-Nearest Neighbours, and the SVM.

The first studies that investigated fraud detection (Sohl & Venkatachalam, 1995; Fraser et al., 1997; Fanning & Cogger, 1998; Zhang et al., 1998) heavily centred on statistical models, for example, neural networks and logistic regression (Yue et al., 2007; Hoogs et al., 2007; Quah & Sriganesh, 2008).

Recent studies on detecting fraud are varied concerning their methods, even though the former techniques are still accepted (West, 2015). The newest research in the literature, such as those conducted by Kirkos et al. (2007), Bose and Wang (2007), Cecchini et al. (2010), Ravisankar et al. (2011), Glancy and Yadav (2011), Humpherys et al. (2011) and Huang (2013), examine fraudulent financial statement by using classification methods to identify fraud.

Evaluation of the effectiveness of different fraud forecast algorithms has been researched. Kotsianis et al. (2006) utilises 123 non-fraud and 41 fraud firms in Greece, with the best algorithm being C4.5 (91.2%), and subsequently RIPPER (86.5%), with low accuracy of ANN (73.4%) and relatively low logistic regression (75.3%). The percentage of fraud firms in the Kotsianis et al. (2006) study (25%) were more significant, implying 0.6% of all firms are fraudulent (Bell & Carcello, 2000). The type I and type II error costs ratio are 1:20 and 1:40, respectively (Beneish, 1999; Bayley & Taylor, 2007)

Kirkos et al. (2007) ascertained Greek's manufacturing firm's involved in fraud. This shows that fraud accuracy and non-fraud accuracy of 91.7% & 88,9% (Bayesian Belief Network) outclassed 82.5% & 77.5% (ANN) and 75% & 72.55 (Decision tree), making type I and type II errors to be practically the same, implying a virtually equal number of non-fraud and fraud firms (Kotsianis et al., 2006).

A different researcher has used a different approach to ascertain financial report fraud using Chinese companies (Ravisankar et al., 2011; Bose and Wang, 2007). While Cecchini et al. (2010), Glancy and Yadav (2011) and Humpherys et al. (2011) also applied the technique of text mining to examine the fraudulent financial report in managerial statements of U.S.-based companies. Zhou and Kapoor (2011) considered behaviours frequently presented in financial report fraud cases and produced a structure for designing fraud detection methods. This gave rise to the computational fraud detection model designed by Glancy and Yadav (2011), where used a measurable approach for clustering documental and textual data. Humpherys et al. (2011) also examined financial statement fraud in 202 listed firms utilising a model that incorporated Naive Bayes and the C4.5 decision tree. While numerous calculation methods have been developed over the years to detect fraud, their successful implementation is influenced by understanding the problem area. No analysis has been conducted on fraud detection, while prior researchers focussed only on problem representation for machine learning techniques. Hence, we try to deal with this in the study. This working method follows the flow of information in machine learning techniques, starting with data gathering and organisation, selecting features and representation, post and pre-processing machine learning techniques, and performance evaluation. Thus, in this study, for detecting fraud in financial accounting, a comprehensive classification framework in applying the machine learning method is followed.

4.4 Description of Gaps in Research Literature – Why do we use Machine Learning Techniques?

Several accounting types of research like Lin et al. (2015), Purda et al. (2015), Throckmorton (2015), Goel S. (2016), Kim et al. (2016), Hajek P. (2017) and Craja et al. (2020) focus on testing various data mining, and statistical simulations aim at improving the techniques of fraud identification. Specifically, financial report fraud is the sole focus of data mining studies, as it possesses exclusive areas. The only traits are as follows:

1) There is a minor ratio between frauds and non-fraud companies (high-class imbalance)

2) Kinds of fraud may vary.

3) The ratio of false-positive to false-negative classification error cost is minor (cost imbalance)

4) The features which are utilised to spot fraud are rather noisy because attribute values of the same kind may indicate non-fraudulent and fraudulent actions.

5) Fraudsters aim hard to cover the fraud by presenting the fraud firms' attribute values as the ones of non-fraud companies.

Since these traits are unique, it is unclear if the classifiers performing well in other areas can perform well in financial report fraud without an empirical assessment.

Usually, financial statement fraud studies adopt regression logistics as the primary method through which data mining models are put through examination. According to Hajek (2017), many data mining algorithms that have worked as reliable predictors in different aspects have not been examined from the viewpoint of financial statement fraud study. As a result, we do not have enough information about which algorithms are essential to discover what exact conditions one algorithm may be more suitable than another, distinguishing financial statement fraud and those predictors that are effective for different algorithms.

This research compares the capacity of forecasting financial fraud using a data mining algorithm. This study examines the algorithms that provide the most utility and which forecasters are vital in revealing financial report fraud. We adopt machine learning techniques because it is superior at performing deep searches at high speeds. This research also aimed at extending knowledge to utilise machine learning techniques to identify financial report fraud. More so, machine learning is superior at addressing uncertainty as it allows fewer constraints to imposed in tasks, Craja et al. (2020) and exposes weaker hypotheses. Machine learning techniques are also superior at understanding associations and hypothesising concepts from datasets.

The answers will be beneficial to institutions such as HCMC, ASE, etc., and the auditors as the results guide, generating new simulations for financial fraud detection. While predictors & algorithms can be used to improve customer selection, analytical procedures, and planning audits, the ASE and HCMC can use the findings to assess if the firm probably commits financial report fraud.

During the last three decades, the statistical process has been utilised in many survey types of research by economic and accounting researchers to face categorisation issues in these areas. Many categorisation methods have been put forward to forecast economic suffering applying the data and ratio which come from financial reports such as univariate methods (Beaver, 1966), multivariate methods, multiple linear discriminate methods (MDA) (Altman, 1968; Altman, Edward, Haldeman & Narayanan, 1977), multiple failures (Meyer & Pifer, 1970), factor analysis (Blum, 1974), logistic failure (Dimitras, Zanakis & Zopounidis, 1996) & stepwise (Laitinen & Laitinen, 2000). Nevertheless, severe expectations involving traditional statistics, such as the structure of linearity, ordinariness and autonomy amid variable predictors, restrict their use in real-time (Hua et al., 2007). Nonetheless, these statistical ways lead to many reasoning drawbacks, and its mistake rate is relatively high. Recently, however, some surveys have used machine learning methods to identify FFS and, in that way, decrease reasoning mistakes. Furthermore, the methods with no statistical assumptions involving data combination (statistical approach) have been applied as a classifier, implying the machine learning methods have a positive categorisation effect.

Furthermore, West (2015) considered that although statistical and computational intelligence techniques share many similarities, the primary point of difference between them is that statistical methods are more firm than rapidly learning and adapting methods such as the computational approach.

CI – machine learning approach is a repeated procedure in which development is outlined by detection, using automatic or manual methods. CI – machine learning methods are mainly beneficial when used in an examining analysis scenario where there aren't any prearranged concepts about what will form an 'interesting' result (Kantardzic, 2002). The utilisation of CI – machine learning methods for economic categorisation is a productive survey filed. Many law impositions and particular analytical units, which detect fraudulent activities, have also effectively applied data mining. Nonetheless, in contrast to other investigated areas, e.g. Bankruptcy forecast or economic suffering, the carried out on the implementation of CI – machine learning methods for the management of fraud realign has been relatively small (Calderon & Cheh, 2002; Koskivaara, 2004; Kirkos & Manolopoulos, 2004).

4.5 Advantages and Disadvantages of Machine Learning Techniques

Several statistics-based techniques resolve the two categorizations involving solvency assessment, credit condition and bankruptcy of an enterprise. Traditional statistics are the most famous techniques, such as Logit and Probit Models and Discriminant Analysis, and computational intelligence methods that include non-parametric statistical models, such as neural networks. Machine learning methods, such as K-nn, SVM, DT, RF, are "new", promising, non-linear and non-parametric classification techniques that show good results. As in different sciences (electric load forecasting, medical diagnostics, visual character recognition, e.t.c), solvency & bankruptcy are of interest in predicting financial report fraud. Using FFS detection, these classification techniques' develop a function that can accurately separate by benchmarking their score values and the distance between fraus and non-fraud firms. The precision score decreases information contained in the financial statements to a simple pointer.

A classification technique's selection for the prediction of FFS poses a challenge, as making a choice appropriately when the data is available can immensely assist in improving the practice's accuracy. Varying categorization procedures can be incorporated to enhance overall performance in predicting fraudulent financial statement. With machine learning techniques, several acceptable models with varied performance features are available to make a choice. As suggested in the No Free Lunch Theorem, the lack of a learning algorithm that can consider being universally best occurs. Therefore, even those considered best can perform poorly with specific problems, while simulation can perform better even with reduced average performance on a few issues. This research tested various machine learning approaches. The present work implies comparing the Naive Bayes and Logistic Regression methods and other machine learning approaches, like SVM, k-nearest neighbours, random forests and decision trees. Therefore, in this section, we refer to the benefits and shortcomings of each method.

According to Luis Eduardo Juarez Orozco et al. (2018), the main advantages and disadvantages of the methods of machine learning techniques are:

Table 7: Advantages and Disadvantages of Machine Learning Techniques

Learning Type	Purpose	Algorithm	Advantages	Disadvantages
Supervised	Classification	Logistic Regression	• Good performance with small datasets • Its output can be interpreted as a probability	• Data assumptions are needed to be complied • It can only provide linear solutions
		K-nn	• Intuitive algorithm	• Number of neighbours must be defined by user • High relative computational complexity
		Naives Bayes	• Performs well in small datasets if conditional independent assumption holds	• Assumption of independence between features
		Support Vector Machines	It can provide non linear solutions	• To achieve good performance they require knowledge about the Kernel employed
		Decision Tree	• They can handle categorical features • Few parameters to tune • They perform well in datasets with large number of features	• Interpretability of ensemble can be questioned
	Regression	Linear (LASSO)	• Good performance with small datasets	• Data assumptions are needed to be complied • Can only provide linear solutions

4.6 Classification Cost

It is essential for a fraud detection model to minimise both types of misclassification errors. There are two errors for detecting the correct percentage in the classification of an FFS. Type I Error is the misclassification of an FFS as non-FFS, whereas type II Error comprises the misclassification of non-FFS as an FFS. Type I and II Errors are presented in Table 8 given below.

The following are the four potential classification outcomes (Table 8) when a binary problem such as fraud is present:

- TP (True Positive): When a fraud company is correctly classified as a fraud company.

- FN (False Negative): When a fraud company is incorrectly classified as a non-fraud company (Type I error).
- TN (True Negative): When a non-fraud company is correctly classified as a non-fraud company.
- FP (False Positive): When a non-fraud company is incorrectly classified as a fraud company (Type II error).

The TP, TN, FN and FP. FP and TP classifications are associated with variegated classification costs that entail investigation costs Ci suffered to determine a fraudulent company. FN classification has fraud costs Cf for recognising specific missed fraud activity that later becomes costly. FP classifications might have Cw costs when a firm is wrongly accused of fraud. Overhead costs such as data loading, computer equipment, running the classification algorithm, etc., are involved in all classifications. The proportion of these cost influences the assessment and training of classifiers (Provost et al., 1998). Two classifiers with different costs can yield different categorisation from the same algorithm.

Table 8:Types of Misclassification Errors

Observed	Predicted	
	FFS	Non-FFS
FFS	Correct classification	Type I Error
Non-FFS	Type II Error	Correct classification

4.7Methodology– Data

The detection of financial statements fraud is complicated or even not possible by applying the first-principles approach. Consistent with the Institute of Internal Auditors (2001), auditors use the techniques below to unveil the relationship between incompatible financial data.

- Compare the information from the current and previous periods. The amount from the last period results from the current period anticipations.
- Comparison of recent period information with budgets includes modifications for estimated curious events and transactions.
- The relationships' research between information elements. Some specific accounts vary concerning others. This occurs concerning a singular financial statement as well as across many financial statements. For example, it can expect commissions to differ differently concerning sales.
- The study of financial information's relationships with suitable-financial knowledge. The non-financial measures are, in general, produced by an outside source. One example of this includes retail stores, in which expected that the sales would vary following the square feet available in terms of shelf space.
- Comparison of similar information derived from the sector in which the organisation operates. The average data in industries are reliable in the case of stable sectors. However, months required by the sector trade relations to analyse, gather and make known the relevant information. Consequently, as a result, the reception of the available data might not occur on time.
- Comparison of similar information that is available for different organisational units. If a company has several stores, it might be possible to compare its different stores. Consequently, should perform sufficient audits on the 'model' store to ensure an appropriate standard.

Concluding, the techniques which are used by fraud examiners to detect fraud have many gaps. In contrast, computational intelligence and measurements enable prompt detection of fraud to reduce associated costs.

However, we can assume a connection between financial features and the absence or existence of fraud in finances (outcome). The possible connection between these attributes and the development are not known in detail due to inherent uncertainty

(Hammer &Zhang,2005; Magder & Hughes, 1997; Parsons, 1996; Ren et al., 2009; Villmann, 2007). Consequently, we have to deal with the presented problem as a 'black box' system. The system's input comprises a set of specific attributes, whereas the output is the outcome of these attributes caused by the system that is not precisely known. The only knowledge we have about the system's operation arises from the specific observations regarding which outcomes cause-specific inputs (attributes). The aim of modelling is building a model for simulating the unknown system, that is, a model that delivers the same outcome as the unknown system on a given data set of observations.

We formulate fraudulent financial statement detection as a classification problem, assuming that the absence or the existence of fraudulent financial statements depends on specific quantitative financial attributes. These attributes, as presented in Table 9, comprise the input to the classifier. Therefore, the classifier's output is either '0'=Non-FFS or '1'=FFS, representative of the absence or the existence of fraud, respectively. If historical data (for instance, in the form attribute-label) exist, then the classifier's efficiency channelled to raising the chance of seizing the opportunities of preventing loss by identifying and verifying potential financial fraud.

Many issues arise when building a model on a given data set for capturing the input-output relationship. Some of the most important among these issues have been described in the following subsections and how we handle them in this study.

4.8 Mathematical Notation

Throughout this section, we employ boldface and lowercase (small) letters to denote vectors, boldface and uppercase (capital) letters to represent matrices, regular uppercase(capital) letters for sets and standard lowercase(small) letters for numerical variables.

Consequently, we indicate the set of attributes as a m-dimensional vector $\boldsymbol{x} \in R^m$. A particular component x_j of the vector corresponds to a specific attribute. That is, $\boldsymbol{x} = [x_1, x_2, \dots, x_j, \dots, x_m]$, where$j = 1,2, \dots, m$. The output y of the classifier is binary, taking the following two potential values:0 or 1,$y \in \{0,1\}$. Suppose the sample is$D$ of $N$of real-world companies. The sample includes the companies that exhibit FFS as well as the companies for which non-FFS is observed. A specific company $\boldsymbol{d}_i = [\boldsymbol{x_i}, y_i] \in \mathbb{R}^{m+1}$ is considered as a datum or an instance and could be represented as a vector of $m + 1$ components. The first m components are as follows: $\boldsymbol{x}_i = [x_{i,1}, x_{i,2}, \dots, x_{i,m}]$ correspond to the attributes of the company, whereasthe last component y_i corresponds to its label.Moreover,$\mathbb{R}, \mathbb{N}, \mathbb{Z}$ are used to denote the set of real, physical and integer numbers, respectively.

4.9 Model Evaluation

A model is a parameterised function that maps a given attribute vector to a label; it is provided that such a mapping exists. The model parameters are computed to perform the most accurate possible mapping for the existing observational data set. This process is usually called training. A standard measure for evaluating the training performance is when the training success classification rate is defined as the number of success classifications in the number of observations.

The generalisation capacity is defined as its success classification rate on new “unseen” instances. Both the training and the generalisation capacity of a model depend on the model’s structure and the selected observational dataset. The most common problem associated with a particular model structure is the problem of “overfitting”. This problem usually arises when a model has a much more complex system (e.g. adjustable parameters) than is necessary. In such a case, the model might demonstrate a noteworthy performance on the ‘known’ training data but remarkably poor generalisation performance on any new "unseen" instances. We adopt the k-fold cross-validation technique for evaluating a particular model to reduce the risk of 'overfitting'.

Given a data set $\mathcal{D} = \{\boldsymbol{x}_i, y_i\}, i = 1,2, \dots, N$ of N observational instances and a model $\hat{y}_i = f(\boldsymbol{x}_i)$, we can compute the average success classification rate of the model on $\mathcal{D}$ as follows:

$$SCR(f, \mathcal{D}) = \left(\frac{100}{N} \sum_{i=1}^{N} I(y_i, \hat{y}_i) \right) \% \qquad ((1)$$

where $y_i, \hat{y}_i$ is the actual and model's output for thei^{th} datum, respectively. The function$I(.,.)$is the identity function, which is defined as follows:

$$I(a, b) = \begin{cases} 1 & if \quad a = b \\ 0 & if \quad a \neq b \end{cases} \qquad (2)$$

When using K-fold cross-validation, the original data set $\mathcal{D}$ is divided into K-equal and mutually exclusive subsets as follows: $\mathcal{D}_1, \mathcal{D}_2, \dots, \mathcal{D}_K$, where $\mathcal{D} = \mathcal{D}_1 \cup \mathcal{D}_2 \cup \dots . \cup \mathcal{D}_K$. The cross-validation process requires the construction of K models. Each model $f_k, k = 1, \dots, K$is trained on the subset $\mathcal{D}_{tr,k} = \mathcal{D} \backslash \mathcal{D}_k$ and is tested on the unseen subset $\mathcal{D}_{ts,k} = \mathcal{D}_k$ by computing its success classification rate $SCR(f_k, \mathcal{D}_k)$ from Eq. ((1). Finally, the average success classification rate $CVSR(f)$, which is computed by Eq. (3), is the overall evaluation measure of the model f on $\mathcal{D}$.

$$CVSR(f) = \frac{1}{K} \sum_{i=1}^{K} SCR(f_k, \mathcal{D}_k) \qquad (3)$$

A commonly used differently from the K-fold cross-validation approach is the bootstrap cross-validation. The testing and training folds are not mutually exclusive but include randomly selected samples. We prefer K-fold cross-validation delivers less biased results (pessimistic) than bootstrap (optimistic) and as it guarantees that a will offer all samples both for training and testing. The essential drawback of K-fold cross-validation is its computational complexity, especially when k it is large. On the contrary, the risk of biased results occurs when K is small (e.g. $K = 2$). Nevertheless, it has been experimentally verified that a value of $K = 5$ offers an adequate settlement between computational complexity and the risk of getting biased results (Kohavi et al., 1995). We use the measure given by Eq. (3) for evaluating models on a given data set throughout this study.

4.10 Candidate Attributes

One of the most critical decisions when learning from observational data comprises selecting attributes (or features or variables) as inputs to the model. Redundant attributes raise the complexity (dimensionality) of the issue and, consequently, the model's complexity. Moreover, some attributes may be contradictory to one another, thereby reducing the model's performance. Several attribute selection techniques exist for detecting significant attributes from aspiring attributes. However, the definition of the initial set of attributes (candidate attributes) can be explicitly conducted by specialists based on experience, knowledge and intuition.

Overall, in our research, the selection of candidate attributes is centred in previous studies. Previous studies (Beneish, 1999; Fanning & Cogger, 1998; Feroz et al., 1991; Lenard & Alam, 2009; Persons, 1995; Ravisankar et al., 2011; Spathis et al., 2002; Stice, 1991; Wells,2005) did not agree on the commonly accepted attributes (financial ratios)related to the detection of the FFS. This affirms that different researchers utilize different attributes for investigating fraud (financial accounts or ratio). Barnes (1990) stated that the criteria change as time passes, as they are affected by microeconomics or macroeconomics changes, such as inflation, technology and fiscal policy.

Therefore, this study adopts the related attributes that are ratios or financial accounts based on prior reviews on the FFS, such as those conducted by Kinney (1989), Loebbecke et al. (1989), Feroz et al. (1991), Stice (1991), Persons (1995), Fanning and

Cogger (1998), Spathis (2002) and Spathis et al. (2002), possessing proposed pointers in detecting FFS. Some attributes are considered to be more likely to lead to the falsification of financial statements. Beasley et al. (1999) reported that the FFS is a typical falsified statement and contains changes in revenue and balance sheet accounts. According to their financial categories, the financial ratios and financial accounts examined in this thesis are presented in Table 9.

Table 9: Financial ratios and financial accounts that are associated with detection of FFS.

Financial ratios and financial accounts			
1a. Profitability ratios (Return of sales)			
Net profit/sales	NPSAL (x_{20})	Z-score (Altman 1968,1983)	z-score (x_{31})
Gross margin	GM (x_{13})	**4. Activity ratios**	
Earnings before interest and taxes	EBIT (x_{28})	Inventory	INV (x_{32})
Net profit after tax	NPAT (x_{33})	Inventory/sales	INVSAL (x_9)
1b. Profitability ratios (Return of investment)		Sales to totals asset	SALTA (x_{23})
Ebit /total assets	EBITTA (x_{29})	Account receivable/sales	RECSAL (x_8)
Gross profit/total assets	GPTA (x_{18})	Sales minus gross margin	COSAL (x_{14})
Net profit/total assets	NPTA (x_{19})	Sales	Sales (x_{12})
Net income/fixed assets	NIFA (x_{25})	Sales growth	SALGRTH (x_{11})
2. Liquidity ratios		**5. Structure ratios**	
Current assets/ current liabilities	CACL (x_{24})	Inventory / total assets	INVTA (x_{10})
Cash/total assets	CASHTA (x_{26})	Total assets	TOAS (x_{15})
Quick assets/current liabilities	QACL (x_{27})	Log of total assets	LTA (x_{16})
Working capital	WCAP (x_{21})	Equity/total liabilities	EQLIAB (x_{30})
Working capital/total assets	WCTA (x_{22})	Net fixed assets/ total assets	NFATA (x_{17})
3. Solvency ratios		Equity	EQ (x_3)
Total debt	TODE (x_1)	**6. Investment ratios**	
Logarithm of total debt	LOGDEBT (x_2)	Net profit/EPS	EPS (X_{35})
Total debt / total assets	TDTA (x_5)	Price/book value	PBV (X_{36})
Long term debt / total assets	LTDTA (x_6)		
Short term debt / total Assets	STDTA (x_7)		
Debt to equity	DEBTEQ (x_4)	Sector	Sector (x_{34})

4.11 Data Collection/Description

Samples should be collected in numbers that are sufficient after the definition of candidate attributes is established. These samples comprise raw data and usually need pre-processing to detect potential outliers and missing values. One more essential pre-processing data step is the attributes normalisation. We would analyse this procedure in detail in the next section, 4.12.

The collection of the data sample expected to make models that can detect fraudulent financial statements. For this cause, numerous factors have studied—one of the essential elements in companies that affect their financial profile. Our primary sources for data comprised the published financial statements and their notes from the ASE database.

Our sample included data from firms in Greece listed on ASE during 2002 and 2015. Our final sample includes 2470 observations. We present the sample description in the following tables, namely,10a and 10b, after excluding firms in the industies of banking, utilities and financial services from the sample. Table 10a is the initially collected sample that included 231 firms, and 3234 observations have been presented. Then, we exclude the observations with missing value and outliers according to the procedure that we analyse in the following Section 4.12, and the final sample is provided in Table 10b.

Table 10a:Sample description

Industry	Number of companies/industry	Sample Selection No of Observations	Missing values	Outliers
Industrial goods and services	19	294	20	25
Retail	13	182	35	17
Construction and materials	33	462	87	41
Media	14	196	44	15
Oil and gas	3	42	0	3
Personal and household goods	47	658	126	70
Travel and leisure	12	182	30	13
Technology	27	364	62	29
Telecommunications	1	14	5	4
Food and beverage	28	364	36	28
Health care	8	126	6	13
Chemicals	9	126	8	9
Basic resources	17	224	11	27
Total	**231**	**3234**	**470**	**294**

Table 10b: Percent of the companies per industry (final sample)

Industry	Number of observations (without missing values & outliers)	Percentage
Industrial goods and services	249	10.08
Retail	130	5.27
Construction and materials	334	13.52
Media	137	5.54
Oil and gas	39	1.58
Personal and household goods	462	18.71
Travel and leisure	139	5.63
Technology	273	11.05
Telecommunications	5	0.20
Food and beverage	300	12.15
Health care	107	4.33
Chemicals	109	4.41
Basic resources	186	7.53
Total	**2470**	**100.00**

Following the studies conducted by Kirkos et al. (2007) and Spathis (2002), the determination of fraudulent financial statement based on the next parameters:

- Inclusion opinions in auditors' reports of serious doubt concerning the accuracy of financial records,
- Tax authorities observations concerning serious taxation intransigency, which seriously altered financial statements of the company's,
- Implementation of Greek law concerning undesirable net income
- Addition of firm in ASE 'negotiation suspended' and 'under observation' for reasons related to falsification of the firms's financial data and
- The auditor's company's size as a criterion: If four big auditor firms have controlled the firm, such as Ernest & Young–PriceWaterhouseCoopers and Deloitte–KPMG Grant Thornton has price 1; otherwise, it has price 0.

We characterised a firm as a fraud firm if it exhibits two and more from the above criteria. We chose this limitation, as the negative net worth, tax issues and small-sized auditors may also indicate inferior liquidity and debt problems, but they do not necessarily mean fraud. Consequently, if the firm has a minimum or sums up two or more criteria, it is more likely to be fraudulent. Therefore, our sample comprises firms characterised as fraud firms, as they met more than two of the above criteria.

We searched for non-fraud samples after the selection of the fraud sample from the same sources. Also, non-fraud enterprises collected by applying the matching method (Sibley &Burch, 1979; Hunt &Ord, 1988). The matching method is a frequent application in financial classification research, like mergers, acquisitions, and bankruptcy, etc. (Altman, 1968; Beaver, 1966; Bhargava et al., 1998; Gaganis, 2009; Hunt & Ord, 1988; Kira & Morin, 1993; Levitan & Knoblett, 1985; Monroe & the, 1993; Rubin, 1973a; Rubin 1973b; Sibley &Burch, 1979; Zopounidis et al., 1998). There are two main reasons behind our apply the matching method. Firstly, it is the time needed and the high cost for selecting samples (Bartley &Boardman, 1990). Secondly is the higher information content in this sample than a random sample (Cosslett, 1981; Palepu, 1986). However, the matching method has been subject to some criticisms. Ohlson (1980) stated that the criteria that applied for the matching method tend to be arbitrary. Ohlson (1980) also said that there is no apparent advantage process of the matching method. Moreover, he suggested that using different factors as independent variables of samples is preferable for matching.

Despite the criticisms mentioned above-presented by Ohlson (1980), we can consider that in random samples of enterprises that have not falsified statements, the researchers can select the enterprises based on size. Based on the above theory, our primary purpose is to construct the following two samples: the training sample and the testing sample.

Table 11: Descriptive Statistics

Attibutes	Mean	Std. Dev.	Min	Max
Total debt	1.03E+08	3.60E+08	66690.27	9.81E+09
Logarithm of total debt	7.517817	0.6675292	4.82	9.99
Equity	6.85E+07	1.79E+08	-4.51E+08	2.13E+09
Debt to equity	2.276962	17.89093	-121.88	433.26
Total debt / total assets	0.6366262	1.24711	0	52.25
Long term debt / total assets	0.2035399	1.028045	0	50.09
Short term debt / total assets	0.4764723	0.9242521	0	16.21
Account receivable/sales	2.591551	3.113205	-2.09	35.28
Inventory/sales	0.6108708	10.5836	0	513.13
Inventory / total assets	0.1211057	0.1518712	0	2.89
Sales growth	0.8068327	5.574254	-1	207.79
Sales	1.37E+08	6.86E+08	0	9.90E+09
Gross margin	0.1282463	2.443636	-109.42	3.69
Sales minus gross margin	1.20E+08	6.60E+08	0	9.58E+09
Total assets	1.67E+08	4.39E+08	592436.8	7.05E+09
Logarithm of total assets	7.828457	0.5590462	5.77	9.85
Net fixed assets/ total assets	0.3142973	0.2600676	0	5.77
Gross profit/total assets	-0.0295788	0.243275	-4.48	2.01
Net profit/total assets	-0.0407047	0.3103408	-10.73	2.01
Net profit/sales	-0.8136655	8.27425	-174.33	93.47
Working capital	6069249	8.95E+07	-1.10E+09	1.23E+09
Working capital/total assets	0.0013528	0.8706237	-13.38	4.95
Sales to total assets	0.625002	0.8207337	-1.82	8.77
Current assets/ current liabilities	1.898218	2.609291	0	38.6
Net income/fixed assets	8.598384	42.12458	0	792.63
Cash/total assets	0.0492021	0.0752455	0	0.82
Quick assets/current liabilities	1.456655	2.223752	-0.28	33.82
Earnings before interest and taxes	-0.5130255	5.89265	-174.28	17
Ebit /total assets	-0.0016687	0.1550494	-2.57	1.08
Equity/total liabilities	2.21853	6.890877	-0.93	95.75
Z-score	3.789243	5.30254	-38.53	70.97
Inventory	1.88E+07	7.96E+07	0	1.43E+09
Net profit after tax	-733583	4.67E+07	-1.51E+09	6.31E+08
Sector	5.454435	3.562599	0	12
P/E	-134.1495	11647.37	-570165.2	78097.69
Price/book value	1.95497	10.32909	-85.97	304.72

Therefore, the similarity period is the main criterion for the two samples (Stevens, 1973). The standard of period refers to the changes in a country's macroeconomic environment and whether it impacts the economic conditions or business decision-making. There is also one more main criteria related to the industry and the total assets of a business. Gautschi and Jones (1987) and Stice (1991) stated that the industry and its size are the most critical factors for the matching method.

Finally, we checked the ratios for endogeneity. We group ratios as appeared in the previous Table nine. to review for endogeneity. We followed three steps to prevent endogeneity. First, endogeneity tests implemented. The H0 has exogenous variables (H0: variables are exogenous). If p-value was low H0 rejected . Second, we checked the first-stage regression to check if the instruments are weak. We studied the correlation between endogenous variables and the tools and by using the Partial R-square. We rejected the H0 if the F-statistic is most extensive from the critical value. The final step checked by Sargan and Basmann for the endogeneity entails performing tests for overidentifying restriction tests. The H0 established the validity of the instruments and mentioned that the model is correctly specified. Moreover, the results appear in Tables. 29-34. of the Appendix. Consequently, the sample does not show endogeneity.

We also decide to use binary classification as our goal is to create machine learning techniques to predict fraudulent financial statements. We have two possible values in the sample as non-fraud and fraud companies. The sample of the two categories (non-fraud and fraud companies) are predefined with the above criteria (pp 105-106). We decide to use binary classification as our dataset has two class labels (0=non fraud and 1=fraud). So our goal of binary classification is to classify our data for fraud and non-fraud. Binary classification is the most common and effective method in the appliance of machine learning techniques. The data used in the algorithms (training set) classified to determine the output. We will use the output later in the classification of new models in the same classes. Each new instance categorizes with the knowledge provides by the training set.

4.12 Data Pre-processing

Data pre-processing involves several steps to prepare clean data and normalise the raw data before it is used for modelling.

4.12.1 Missing values. The most frequent subjects that data pre-processing is missing values. This study completely removed a sample from the data set if one or more sample attributes had missing values.

4.12.2 Normalisation. The normalisation of attributes is an essential pre-processing step when applying algorithms based on metrics (distances). It guarantees that attributes with a large domain would not override the attributes with a small domain. In this study, we performed the normalisation step by linearly mapping each attribute's value from its actual range within the interval [0,1].

4.12.3 Outlier detection. Outlier detection is a difficult pre-processing step. The difficulty arises from an unclear definition of an outlier (Koufakou &Georgiopoulos,2010; Zimek et al., 2012). This study considered those instances (companies) as outliers who have insignificant or out-of-feasible range values for some attributes. The outliers eliminated from the data set before the application of every modelling techniques.

4.13 Attribute Selection

The first step in attribute selection is the designation of those attributes that affect the system's output based on experts' knowledge, experience and intuition. This step, which a human expert exhaustively performs, generates candidates' attributes. The next step is evaluating candidates' attributes for selecting an optimal subset by including only those attributes that are necessary and sufficient for describing the input-output relationship efficiently. This step can be computationally accomplished by applying several data analysis algorithms.

Usually, a subset of the initial set of candidates' attributes affects the target. This is because some of the candidates' attributes are interdependent of one another or because some of them are irrelevant to the target. Locating the smallest subset of attributes necessary and sufficient to describe the target comprises the task of feature or attribute selection. The inclusion of redundant attributes in the building process of a model involves many risks. The obvious risk is its increased complexity, which, therefore, makes it vulnerable to overfitting. The cascade result of overfitting is the poor generalisation performance of the model. A deeper issue is that redundant attributes may be deceptive (contradictory of one another) for some instances, thereby decreasing the overall performance of the model. Hence, the task of attribute selection is fundamental and has gained the interest of the machine learning community, as can be perceived from the studies conducted by Kwak and Choi (2002) and Chandrashekar and Sahin (2014). Over time, the attribute selection methods have been divided into the following three major categories: a) filter-based, b) wrapper-based and c) embedded (Kohavi &John, 1997).

Filter-based methods compute the correlation between a particular attribute (variable to predict target) and the target. They are independent of any model and are fast and robust to overfitting. The main drawback of these methods is that they are univariate and may ignore the potentially interdependent attributes. The most widely used filter-based methods are Pearson-, Spearman- and Kendall's-τ correlation coefficients. The correlation between every attribute and the output was jointly computed with a statistical test of significance. The statistical test of significance is based on estimating the probability ($p - value$) of accepting the null hypothesis as follows:

H_0 =**{The specific attribute is by chance correlated with the output}.**

If the $p - value$ is smaller than an arbitrarily predefined threshold a (usually $a = 0.05$) for a particular attribute, then the null hypothesis is rejected for that attribute.

Consequently, that attribute is considered statistically significant. Specifically, the Pearson approach is based on two assumptions: a) the tested attributes follow a normal distribution, and b) they have a linear relationship with the output. In contrast, Spearman's and Kendall's approaches are non-parametric, as specific assumptions on the distributions of attributes are not required. Another drawback of this family of methods is that the threshold for accepting the null hypothesis is arbitrarily defined. Consequently, the decision made to accepting or rejecting an attribute is difficult, especially if the value for a particular attribute is close to the threshold.

The embedded methods perform attribute evaluation as an "*effect*" that arises from the model's creation process (Guyon &Elisseeff, 2003). This category includes any modelling approach in which attribute selection is an essential part of the model's structure identification task (e.g.the models based on Tikhonov regularisation [Tikhonov et al., 1998], such as those proposed by Efron et al., 2004; Vapnik, 2000). This family of methods usually assigns relative importance to attributes, according to the numerical coefficient that accompanies each attribute. However, they typically fail to provide a binary and clear decision on which attributes are essential or not when some coefficients have similar values.

Wrapper-based methods employ a model that operates as a 'wrapper'. Different subsets of attributes are gradually presented to the model and are evaluated according to the model's performance. The subset with the lowest cardinality and the maximum performance (usually cross-validation score) is selected as the set of significant attributes. We underline that significant attributes depend on the selected wrapper when this family of methods is used. Although the decision is model-dependent, it has been widely recognised that wrapper-based methods are more accurate than filter-based ones (Guyon &Elisseeff, 2003; Kohavi & John, 1997).

Evaluating all possible subsets of attributes is a computationally intensive task. For example, different subsets need to be evaluated for candidate attributes. For each attribute combination, a different model should be built and evaluated. This may be computationally overwhelming even for a small number of observations. Therefore, some approaches perform the role of addressing this problem, including nonlinear optimisation methods (e.g. genetic algorithms) (Alexandridis et al., 2005; Papadakis et al., 2005). Forward inclusion and backward elimination (Nakariyakul &Casasent, 2009) are two easily applicable heuristic techniques for performing sequential searching for the best feature subset. These two approaches are briefly discussed below.

We used wrapper-based methods, as they tend to deliver more accurate results than filter-based ones (Monroe &Teh, 1993). A particular model was used as a wrapper, and different subsets of attributes were sequentially presented to it according to a forward inclusion approach (Section 4.13.2). Consequently, we evaluated each attribute combination according to the measure described in Eq. (3). As described in Section 4.14, several models were used as wrappers, as we did not a priori know the most appropriate model for our data, consistent with the" 'no free lunch theorem" (Wolpert, 2002). We adopted the best model, as evaluated in terms of Eq. (3), jointly with the respective selected attributes as the solution to our problem.

4.13.1 Recursive elimination (RE)

Given a model and a dataset of m attributes, the recursive approach operates as follows: the first level (root) includes all m attributes, and the respective model is built by using all attributes. The cross-validation score of the model is used as a baseline score. At the next level, one attribute at a time is eliminated from the set of the previous level, therebycreating m models. Each model includes $m - 1$ attributes at this level. For each one of the $m - 1$ models, the cross-validation score is computed. If the score of a particular model(s) is/are not worse than the score of the previous level, then the corresponded subset(s) of attributes is/are entitled to further elimination. The entitled subset(s) is/are further expanded by eliminating one attribute at each level. The procedure terminates either when the cardinality of the subset that is being evaluated is 1 or when a worse score is achieved for the next level by eliminating any attributes. The main drawback of this procedure is that when a particular attribute is removed from a subset, then that attribute never has the chance to be jointly evaluated with another subset of attributes in the future. The advantage of RE is that it is computationally less expensive when compared with the 'forward inclusion' (FI) method (which has been described in the next section). This advantage makes RE more appropriate than FI for large sets of candidates' attributes.

4.13.2 Forward inclusion (FI). Forward inclusion starts with an empty set of attributes that are stored in the root of a tree. Given a model of m -attributes, the root's descendant nodes are created, each of which stores an individual attribute. For each node, a model is created by using the respective attribute of the node. The model is evaluated by using the cross-validation success classification rate (CVSR) score. The score is computed and stored at the node. The nodes with the maximum score are characterised as "expandable". The descendants of an expandable node are derived from the Cartesian product between two subsets of attributes. One subset includes the node themselves' attributes, whereas the other contains all attributes except the node's attributes. Each descendant node corresponds to a specific element (a subset of attributes) of the Cartesian product. Afterwards, each descendant node is evaluated by creating a model with the subset of attributes of the node. Finally, the respective CVSR score is computed. A descendant is adopted if its score is greater than the score of its parent. Otherwise, the descendant is rejected. The procedure recursively proceeds until no expandable node exists at any level or until all attributes are included. FI is computationally more expensive than RE, but it is safer than RE, search attribute can test itself jointly with the other attributes many times. For this reason, we adopt the FI approach for detecting the actual subset of attributes.

4.14 Description of Employed Models (Wrappers)

We used particular models from established paradigms of machine learning and statistics. More specifically, we used K-Nearest Neighbours (k-nn) as a representative from "instance-based learning", classification and regression trees from the paradigm of "Decision Trees" (DT), Random Forests (RF) from "ensemble methods", the SVM classifier from "kernel-based methods and radial basis functions".We used logistic regression (LR)from statistics and the Naïve Bayes (NV) method from the "Bayesian paradigm". Although many variations exist for each model, we applied the "principal" model, which we considered "representative" for each paradigm.

4.14.1 K-Nearest Neighbours classifier (k-nn). The k-nn is a simple, instance-based discriminative classifier. K-Nearest Neighbor Classifier's main benefit is that it is a very simple classifier that works well on fundamental recognition problems. In contrast, the KNN algorithm's main disadvantage is that it is a "lazy learner". For example, the algorithm is incapable of learning from the training's data and, therefore, it follows the simplistic method of using the data for categorization purposes.

$k - nn$ does not need training, as the whole training set is used for recall. Usually, a set $[\boldsymbol{x}_i, y_i], i = 1, \dots, N$ of known instances$[\boldsymbol{x}_i, y_i]$ is used as the "codebook" on which the recall takes place in the following way: if a new instance $\boldsymbol{x}^*$that is being classified arrives, then its distance, as given by Eq. (4), is computed from each element of the codebook.

$$L_{p,i}(\boldsymbol{x}_i, \boldsymbol{x}^*) = \left|\left|\boldsymbol{x}_i - \boldsymbol{x}^*\right|\right|_p = \left(\sum_{j=1}^{m} \left|x_{ij} - x_j^*\right|^p)\right)^{\frac{1}{p}}, p > 0 \quad (4)$$

The label of the new instance is the major label of the $n-$ nearest to its instances' label of the codebook. The $k-nn$ delivers good results in some cases despite its simplicity. The KNN algorithm would attempt to find the K-closest neighbors with respect to the training data's new instance to predict its label. Consequently, the class label that is predicted will be considered as the commonest label that can be found among the K-closest neighboring points.

The generalisation performance of $k-nn$ strongly depends on the predefined number of neighbours as well as the parameter p given in Eq. (4). both parameters are problem-dependent.

The optimum value of these parameters was computed by using cross-validation in this study. We received the best results for $k=1, p=1$. We reported only the best result at each forward selection tree for simplicity reasons, as the whole tree was too complex to be displayed (e.g. 36 variables were present inthe first level).

4.14.2Naïve Bayes Classifier (NB)

The Naïve Bayes (NB) classifier, which was introduced by McCallum et al. (1998), Zhang (2004) and Manninget et al. (2008), is a simple generative model that performs surprisingly well in some financial applications despite its simplicity (Li, 2010). NB Classifier is fast to train. Therefore, it is quick to classify. It is not sensitive to irrelevant features. It handles real and discrete data, and, NB Classifier takes streaming data well.

NB can be applied, in the domain of classification, under two assumptions. The first assumption is that the attributes $\boldsymbol{x}=[x_1, x_2, \dots x_j, \dots, x_m]$ are conditionally independent of other random variables. The second assumption is that each attribute $x_j, j=1, .., m$ is a random variable that follows normal distribution for each class.

NB computes the conditional probability $P(Y=y_k/X=\boldsymbol{x}), k=1,2, \dots, L$ for classifying a sample $\boldsymbol{x}$ into one of the L available classes.

According to Bayes' law, the conditional probability is given by Eq. (5).

$$P(Y = y_k/X = \boldsymbol{x}) = \frac{P(Y = y_k)P(X = \boldsymbol{x}/Y = y_k)}{P(X = \boldsymbol{x})}, k = 1,2, \dots, L \tag{5}$$

The denominator of Eq. (5) can be omitted,asit has the same value for all attributes and, therefore,it assignsno importance to the final decision. Moreover, the assumption that attributes are independent of one another allows the calculation of $P(X = \boldsymbol{x}/Y = y_k)$ by Eq. (6).

$$P(X = \boldsymbol{x}/Y = y_k) = \prod_{j=1}^{m} P(X = x_j/Y = y_k),\ k = 1, \dots, L \tag{6}$$

NB assumes that the conditional probability $P(X = x_j/Y = y_k)$ for any attribute x_j, whena particular class y_k is given, follows the normal distribution $\mathcal{N}(m_{kj}, \sigma_{kj})$ where m_{kj} denotes the mean and denotes the standard deviation of attribute j for the class k, respectively. m_{kj}, σ_{kj} are calculated from the training samples along with $P(Y = y_k)$, which is computed as the percentage of class k in the number of samples. When a new instance $\boldsymbol{x}^*$ arrives, the probabilities $P(Y = y_k/X = \boldsymbol{x}^*)$ are computed for each class, and the instance is classified to the class that hasthe greater probability value. That is,

$$y^* = \underset{y_k}{\operatorname{argmax}} P(Y = y_k/X = \boldsymbol{x}^*) \tag{7}$$

The most important disadvantage is that it assumes strong attribute independence assumption

4.14.3 Logistic regression Classifier (LR)

Logistic Regression (LR) introduced by Murphy (2012) and Hosmer et al. (2013) is another generative model thatperforms well in several financial applications (Hua et al., 2007). Suppose that an event y has a binary outcome of either "0' or "1". LR is a method for estimating the conditional probability $P(y = y_i|x = x_i)$ of a binary outcome $y_i \in \{0,1\}$of the event y, given that another event $\boldsymbol{x}$ has occurred. Typically, the event $\boldsymbol{x}$ is a vector of observatory variables $\boldsymbol{x} = [x_1, x_2, \dots, x_m]$, which influence the occurrence of y. The binary outcome could either be "0", which represents the outcome that event y will not occur or "1", which represents that y will occur. This statement implies that $P(y = 0|\boldsymbol{x}) + P(y = 1|\boldsymbol{x}) = 1$ in terms of probability.In analysis of mutilple discriminate, this method does not adopt multivariate regularity with equal covariance matrices, one benefit of this method.

LR can easily be adapted to the context of classification problems by assuming that the observational variables coincide with the attributes $\boldsymbol{x}_i$of a particular instance $[\boldsymbol{x}_i, y_i]$and the class label y_i coincides with the outcome (either "0" or "1"). The decision for the class of a new instance, given its attributes $\boldsymbol{x}^*$, is based on the computation of $P(y = 0|\boldsymbol{x}^*)$ or its complement$P(y = 1|\boldsymbol{x}^*)$. For example, if $P(y = 1|\boldsymbol{x}^*)$ is greater than 0.5, then the new instance belongs to class "1". Otherwise, the new instance belongs to class "0". To accomplish this end, there is a needto frame the conditional probability $P(y = 1|x)$ as a function of $\boldsymbol{x}$. If we define $p(x) = P(y = 1|\boldsymbol{x})$,then $P(y = 0|\boldsymbol{x}) = 1 - p(x)$. LR considers that the logit transform is an affine linear function of the components of vector $\boldsymbol{x}$ as follows:

$$\ln\left(\frac{P(y = 1|\boldsymbol{x})}{P(y = 0|\boldsymbol{x})}\right) = \ln\left(\frac{p(\boldsymbol{x})}{1 - p(\boldsymbol{x})}\right) = \ln\big(p(\boldsymbol{x})\big) - \ln(1 - p(\boldsymbol{x})) \quad (8)$$

That is,

$$\ln\left(\frac{p(\boldsymbol{x})}{1 - p(\boldsymbol{x})}\right) = w_0 + w_1x_1 + .. + w_mx_m = w_0 + \boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{x} \quad (9)$$

where $w_0 \in R$, and $\boldsymbol{w} \in R^m$ is a vector of unknown parameters.

Eq. (9) implies that the following:

$$p(\boldsymbol{x}) = \frac{1}{1 + e^{-(w_0 + \boldsymbol{w}^T \boldsymbol{x})}} \tag{10}$$

The parameters $w_0, \boldsymbol{w}$ were computed from the observational data according to the concept of maximum likelihood principle as follows:

Each training datum $[\boldsymbol{x_i}, y_i]$comprises an attribute vector $\boldsymbol{x}_i = [x_1, x_2, \dots, x_m]$ and a class label $y_i \in \{0,1\}$. The probability of the class label is either $p(\boldsymbol{x})$if $y_i = 1$ or $1 - p(\boldsymbol{x})$ if $y_i = 0$. The likelihood function is that of parameters$w_0, \boldsymbol{w}$,and the likelihood is a function$L(w_0, \boldsymbol{w})$, as given by the following:

$$L(w_0, \boldsymbol{w}) = \prod_{i=1}^{N} [p(\boldsymbol{x})^{y_i} \cdot \left(1 - p(\boldsymbol{x}_i)\right)^{1-y_i}] \tag{11}$$

Typically, the log-likelihood $h(w_0, \boldsymbol{w}) = \ln\, L(w_0, \boldsymbol{w})$ is used instead of Eq. (11), aslogarithms turn products into sums. The log-likelihood is calculated by calculating the $\ln(.)$ of the two parts of Eq. (11), which leads to Eq. (12).

$$h(w_0, \boldsymbol{w}) = \sum_{i=1}^{N} [y_i \ln(p(\boldsymbol{x}_i)) + (1 - y_i) \ln\left(1 - p(\boldsymbol{x}_i)\right)] \tag{12}$$

Or, equivalently, we can obtain Eq.((13) by substituting Eqs.(8) and (9) into Eq.(12) as follows:

$$h(w_0, \boldsymbol{w}) = \sum_{i=1}^{N} [y_i(w_0 + \boldsymbol{w}^T \boldsymbol{x}_i) + \ln(1 - p(\boldsymbol{x}_i))] \qquad ((13)$$

The estimation of parameter $w_0, \boldsymbol{w}$is carried out by computing those values of $w_0, \boldsymbol{w}$ that maximise$h(w_0, \boldsymbol{w})$. This is a typical, unconstrainedoptimisation problem and can be solved by using any non-linear optimisation algorithm.

The optimisation can be iteratively computed by using gradient descent as given below:

$$w_0(t+1) = w_0(t) + \lambda \frac{\partial h(w_0, \boldsymbol{w})}{\partial w_0} \quad ((14)$$

$$w_j(t+1) = w_j(t) + \lambda \frac{\partial h(w_0, \boldsymbol{w})}{\partial w_j} \quad ((15)$$

Where $\lambda \in (0,1)$ in Eqs.((14) and ((15) denotes the learning rate, and t denotes the time step (epoch).

Computing the gradients, we obtain the following:

$$\frac{\partial h(w_0, \boldsymbol{w})}{\partial w_0} = \sum_{i=1}^{N} [y_i - p(\boldsymbol{x}_i)] \quad ((16)$$

$$\frac{\partial h(w_0, \boldsymbol{w})}{\partial w_\mathrm{j}} = \sum_{i=1}^{N} x_{ij} [y_i - p(\boldsymbol{x}_i)], j = 1,2, \dots, m \quad ((17)$$

Eqs.((16)and ((17)iteratively compute the parameters. The algorithm converges to a global optimum, as the log-likelihood given by Eq. (12).

4.14.4 SVMs

SVMs introduced by Bartlett and Shawe-Taylor (1999) and Vapnik (2000) are machine learning models that have the structural risk minimisation concept as their basis instead of traditional models that have empirical risk's minimisationas their basis (e.g.mean square error).

The basic advantage of the SVM is that apriori it provides theoretical guarantees on the limits of the generalisation errors inaccordancewiththe VC dimension (Bottou et al., 1994; Chen et al., 2006; Vapnik, 2000). Also, its prediction accuracy is high. SVMs provide a good out-of-sample generalisation, if the parameters C and γ are appropriately chosen. This means that by choosing an appropriate generalisation grade, SVMs can be robust even when the training sample is some what bias. In addition, SVMs has exhibit the fast evolution of the learned target function.

The two-class SVM classifier requires two labels $\hat{y} \in \{-1, +1\}$ for generating the output of the classifier. The output$\hat{y}^*$ of the classifier, given an input vector $\boldsymbol{x}^*$, is computed by Eq. ((18).

$$\hat{y}^* = f(\boldsymbol{x}^*) = sign\left(b + \sum_{q=1}^{Q} a_k y_k \mathrm{K}(\boldsymbol{x}^*, \boldsymbol{x}_k) \right) \qquad ((18)$$

Where $[\boldsymbol{x}_q, y_q], q = 1, \dots, Q$ are selected training instances, namely, support vectors, and $a_q \geq 0, \forall q$ are real numbers weighting the respective support vector. The function $K(\boldsymbol{x}^*, \boldsymbol{x}_k)$in Eq.((18) is a positive definite function (Burges, 1998;Smola &Scholkopf, 1998), namely, a kernel function. The kernel function that is used here is a radial basis function, as given by Eq.(19).

$$K(\boldsymbol{x}, \boldsymbol{y}) = e^{-\gamma \cdot \|\boldsymbol{x} - \boldsymbol{y}\|_2}, \gamma \in \mathbb{R} \qquad (19)$$

The $Q \in \mathbb{N}$ support vectors as well as the respective weights (in addition tothe constant $b \in \mathbb{R}$) were computed from the training instances by solving the constrainedoptimisation problem, as given by Eq. (20) (see the study conducted by Schölkopfet al.[2002] for details). The constrainedoptimisation problem is given as follows:

$$
\text{maximise} \quad \sum_{i=1}^{N} a_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} a_i a_j y_i y_j K(\boldsymbol{x}_i, \boldsymbol{x}_j)
$$

$$
\begin{gathered}
s.t. \\
0 \leq a_i \leq C, \forall i = 1, \dots, N, C > 0 \\
\sum_{i=1}^{N} a_i y_i = 0
\end{gathered}
\tag{20}
$$

Actually, there are two predefined parameters, which are namedhyper-parameters, as follows: the parameter $C \geq 0$ in Eq.(20) and parameter γ in Eq. (19). The parameter C regulates the tolerance of the optimisation process about misclassified data. The C value is a penalty weight for the misclassified data. The parameter γ regulates the width of the radial basis function. The performance of SVM depends on the predefined values of hyper-parameters. In this study, we experimentally computed the optimal values by using cross-validation.

As referred to in the literature, the main disadvantage of SVMs is that they take a long training time. Moreover, it is difficult to understand the learned functions (weights). Weights in financial ratios are not reliable, thus contributing financial ratio score variable. With the Gaussian kernel, the company’s weight is centred on variation in financial ratio value and support vector obtained from the data sample.

4.14.5 Decision Trees (DT)

Decision trees (DT) were first introduced by Breiman et al. (1984) in machine learning. The basic concept of DT, when used as classifiers, involves the recursive partition of the input space into sub-spaces until the samples of each sub-space have the same label.

DT is a simple method to understand and interpret results. DT are valuable even when negligible hard data is available. Therefore, essential insights from decision trees can be generated based on the experts' description of a situation (for instance, its probabilities, costs and alternatives) and their outcome preferences. Nevertheless, the decision tree's shortcomings are: first, they are inadequate in applying regression and predicting continuous values and, second, DT are limited to producing one output per attribute. Also, they exhibit an inability to representing the tests that refer to different objects that are two or more in number.

According to a pre-defined measure, the attribute that better splits the data and the decision of the split point for a given attribute is determined at each step—the algorithm(s) recursively proceed/s until a stopping criterion is met. The measure on which the split is based (e.g. information gain, Gini index, gain ratio), as well as the stopping criterion (e.g. all samples of a node belong to the same class, the number of samples of a node is less than a pre-defined threshold), are the essential differentiators of DT approaches (e.g. ID3, C4.5, CART) (Rokach &Maimon, 2005; Rokach &Maimon, 2014). Strict or loose stopping criteria may lead to under-fitting or over-fitting of the data, respectively. Both cases may lead to poor generalisation performance. The concept of pruning, which was first introduced by Breiman et al. (1984), is an established approach for resolving to select an inappropriate stopping criterion. The underlining idea of pruning is to remove those tree nodes that do not contribute to the generalisation performance.

The 'Gini' information index (Breiman et al., 1984) provides the best generalisation results after cross-validation, and it was adopted as a split criterion in this study. Moreover, we adopted the 'best split' strategy for each attribute that was being split. We split at the point that provides the largest possible information gain ('Gini' value). The number of samples should be at least two for splitting a node. We did not impose tree depth restrictions, and the tree grew until all samples of each leaf belonged to the same class. Finally, no pruning was applied.

The selected variables, as well as their respective cross-validation performance, have been reported in Table 12.

4.14.6 Random forests (RF)

A Random Forests (RF) presented by Breiman (2001) is an ensemble of DT. Breiman (1996) supported that RF is a promising classifier and presents many advantages when it is applied. Some of the RF benefits are as follows: first, it can be performed on big databases effectively. Second, thousands of inputs variables inserted can be adequately handled. Third, it provides an assessment of which variables is vital in the categorisation. Fourth, produces a fair evaluation of generalisation error obtained. Firth calculates closeness for locating outliers. Sixth, healthy to noise and outliers. Seventh, calculative easier than other tree approaches. However, the random forest algorithm major shortcoming is the real-time forecast's slowness due to huge tree figures.

The basic concept of ensembles comprises building some individual classifiers and aggregating their results. It has been widely recognised (Kuncheva, 2004; Witten et al., 2016) that an ensemble of models usually delivers better performance than single models (counterparts) independently. Multiple DT were built at the training time using part of the training dataset either in terms of attributes or instances to construct an RF. The new datum was presented to each ensemble's counterpart to make predictions on the new, unseen data (recall time). The output of each classifier was memorised,and the majority (mode) output of an individual tree was adopted as the output of the ensemble. Among the many existing strategies for building the individual tree, we selected all instances and a randomly selected subset of attributes. We used 15 DT, as that number provided better generalisation results in terms of cross-validation. The specific parameters for building each tree have been previously mentioned in section 4.14.5.

4.14.7 Least absolute shrinkage and selection operator (LASSO)

Robert Tibshinari (1996) was the first researcher who applied Lasso. Lasso is included in embedded methods. Lasso contains two tasks. The first task is the regularization, and the second task is the variable selection. Lasso method has a limitation the sum of the model coefficient should be less than the sum of a fixed value. So this method tends to zero coefficient. The non zero coefficients are the variable selection of the model. The predictor error is minimized with this process. Lasso method has two advantages. The first advantage is that provide good prediction accuracy and second lasso method can increase the model predictability.

The model is linear and has the general form:

$$f(\overline{\boldsymbol{x}}) = \boldsymbol{w}^T \cdot \boldsymbol{x} \qquad (21)$$

where $\boldsymbol{x} = [\boldsymbol{x_1}, \boldsymbol{x_2}, \ldots, \boldsymbol{x_m}]$and $\boldsymbol{w} = [\boldsymbol{w_1}, \ldots., \boldsymbol{w_m}]^{\boldsymbol{T}}$

In a typical least square problem the solution is the resulting of the minimum of the function according to the following equation:

$$\boldsymbol{mse} = \frac{\boldsymbol{1}}{\boldsymbol{N}} \|\boldsymbol{Y} - \boldsymbol{X} \cdot \boldsymbol{w}\|_{\boldsymbol{2}}^{\boldsymbol{2}} \qquad (22)$$

In Lasso method the result is the the minimun of the following function:

$$\frac{1}{N} \cdot \left\|\boldsymbol{Y} - \boldsymbol{X} \cdot \boldsymbol{w}\right\|_2^2 + \alpha \cdot \|\boldsymbol{w}\|_{\boldsymbol{1}} \qquad (23)$$

The coefficient α regulates the weights when coefficients are small. According to the equation 23 we calculate the weights. In the appendix we appear the analytical results.

4.15 Conclusion

This chapter analyses the literature review in Computational Intelligence, in general, and in machine learning techniques, in particular. As we have referred to above in this chapter, statistical and computational intelligence techniques share many similarities. Still, the significant variation involves the flexibility and ability to learn and adapt to changing problem associated with the computational method. Specifically, this thesis compared the performance of various data mining means, including DT, NB, LR, RF, k-nn and SVM. Consequently, we followed a comprehensive classification framework of machine learning techniques adopted in revealing fraud in financial accounting.

Chapter 5 Empirimental Results

5.1 Introduction

This aspect of the study is divided into fives sections. This chapter refers to the experimental results of our research. These results address the first three research questions. The first research question evaluates which financial ratios are connected to the detection of FFS. The second research question referred to the predictive ability of financial ratios on FFS. Finally, the third research question asked whether computational intelligence techniques can prevent and detect FFS. Therefore, Section 5.2 answers the first research question, Section 5.3 answers the other two research questions. Finally, 5.4 comprises the conclusion section.

5.2 Comparison of Factor Importance

Table 12 presents the comparison results from the machine learning' methods. It presents the fraud factors in the different techniques and findings of a comparison of empirical data. Furthermore, Table 12 presents the significance of the attributes that are incorporated into the prediction simulation. The essential category of fraud detection is 'poor performance'. All factor effects are similar to previous studies. The top seven fraud factors include; log of total debt, equity, debt to equity, the log of total assets, net fixed assets to total assets, cash to total assets and sector. Furthermore, the profitability, liquidity, solvency, activity and structure ratios are significant predictors for fraud detection. Specifically, significant ratios that are the most important for FFS appear in Table 12 and are analyzed below.

Managers may be enticed to participate in fraud when monetary difficulties are expected. Leverage proxies result is a fraud analysis indicator. These ratios agree with the studies conducted by Fanning and Cogger (1998) and Spathis (2002), which imply that higher debt to equity ratios indicate fraud firms. Reviews by Fanning and Cogger

(1998), Kirkos et al. (2007) and Ravisankar et al. (2011), the probability of the FFS increases when the levels of debt are higher. However, Persons (1995) claimed that the answer to if increased debt organization is connected to FFS is unknown. A high debt organization amplifies the possibility of FFS as it transfers the danger from the managers and owners of equity to debtors. Executives influence financial report following the need to meet debt agreement increases, suggesting that increased debt raises the chances of FFS. Also, it entails that companies with a total debt to total equity ratio that high reflect an amplified probability of being categorized as fraudulent firms. As mentioned in previous studies, such as Holthausen and Leftwich (1983), Persons (1995), Watts and Zimmerman (1990) and Christie (1990) argued that high debt structure is a likely motivator for FFS. Also, Loebbecke et al. (1989) established that 19% of the sample companies displayed solvency problems. The frequently used ratios for fraud identification include the total debt to total assets (TD/TA) ratio (Dalnial et al., 2014; Gaganis, 2009; Kirkos et al., 2007), the total liabilities to total assets (TL/TA) ratio (Lenard, 2009), and the total debt to equity (TD/Eq) ratio (Dalnial et al., 2014; Kirkos et al., 2007; Spathis et al., 2002).

Unliquidity might incentivize the engagement of managers in FFS. This finding agrees with the study conducted by Kreutzfeldt and Wallace (1986), which shows that the companies suffering from liquidity problems experience more errors significantly in their respective firm's financial statements than the firms that do not have any liquidity problems. The working capital to total assets (WC/TA) and the current assets to current liabilities (CA/CL) ratios mainly measure liquidity (Lenard&Alam, 2009; Ravisankar et al., 2011). More so, Spathis (2002), in a logistic regression study conducted on fraudulent financial statements forecast, claimed that following ratios; i) net profit/total assets (NP/TA) and ii) working capital/total assets (WC/TA), present significant coefficients. Nevertheless, Spathis et al. (2002) suggested net profit/sales (NP/SAL) is also relevant. In this study, FFS's most essential liquidity ratios are working capital, current assets to current liabilities, and cash to total assets.

Managements also participate in fraud for their continued development (Song et al., 2014; Stice, 1991). The companies inability to attain comparable results as prior achievements may enhance management participation in fraud (Stice, 1991). On the other hand, the companies expanding quickly surpass their process observation capacity to offer appropriate supervision (Fanning &Cogger, 1998). Researchers frequently identify fraud with the use of company's activity and effectiveness asset composition ratio and to perceive whether the company maintains growth as follows: the sales to total assets (SAL/TA) ratio, the net profit to sales (NP/SAL) ratio, the net profit to total assets ratio (ROA) and the current assets to total assets (CA/TA) ratio. It was claimed by Kirkos et al. (2007) that manipulation could also affect the gross margin. Researchers used the following as a means of identifying fraud: the gross profit to sales (GP/SAL) ratio and the gross profit to total assets (GP/TA) ratio. Citron (2001) also concluded that the size of the company is statistically important.

Furthermore, lower profits may give incentives to the management to overstate revenue or understate expenses. This approach's basis is the management's expectation is to preserve or raise previous productivity levels (Summers &Sweeney, 1998). In case this expectancy is not reflected by the real performance, it would be motivateFFS. Financial distress acts as a motivation for FFS(Kreutzfeldt &Wallace, 1986; Loebbecke et al.,1989). In this study, the most important profitability ratios for fraudulent financial statements are:

- Gross profit to total assets.
- Net profit to total assets.
- Net income to fixed assets and EBIT to total assets.

Accounts that allow personal assessment is more challenging to audit; therefore, they are disposed to forgery. Accounts receivable, inventory and sales fall into this category. Stice (1991), Feroz et al. (1991) and Persons (1995) claimed that the firms' administration might influence receivable accounts by recording sales that are yet to be made as surplus receivable account (Fanning &Cogger, 1998). Furthermore, Francis and Krishnan (1996) concluded a positive relationship but no statistical significance for the financial ratio inventory to total assets in their research about FFS detection. They also observed a negative association of accounts receivables ratios to total assets. This relation was statistically significant. Loebbecke et al. (1989) stated that receivables accounts and inventory contained 14% and 22% of FFS, respectively.

Many researchers suggested that the management might manipulate inventories (Persons, 1995; Stice, 1991) by recording outdated inventory and inventory with lesser cost. In the studies conducted by Kirkos et al. (2007) and Perols (2011), accounts receivable and records are financial report variables that permit an estimation that would be subjective. Therefore, the ratios that are utilized to determine the FFS comprise the inventories to total assets (INV/TA) ratio, inventories to sales (INV/SAL) ratio and the accounts receivable to sales (REC/SAL) ratio. Gross margin is also prone to manipulation. Organizations should not equally firm's sales with matching the cost of sold goods, thereby increasing gross margin and net income and strengthening the balance sheet (Fanning &Cogger, 1998). We tested the gross margin by using i) the ratio of sales minus the gross margin (COSAL) and ii) the ratio of gross profit/total assets (GP/TA).

Significant results have also been seen in capital to income alternatives to revenue. High receivable account ratio to sale and inventory to sale is in line with this thesis, proposing that increased frequency of influence occurs in receivable accounts. Furthermore, asset composition proxies by inventory to total assets ratios presents noteworthy findings. Also, our study concludes organization size, as determined by total assets, is statistically significant. Finally, ratios' sales growth, sales to total assets sales minus gross margin inventory of net fixed assets to total assets equity to total liabilities and P/E are significant in the detection of FFS.

We also examined two investment ratios. The first is the price-earnings ratio (P/E) and the second ratio is the price/book value (P/B). The P/E evaluates firms that measure their current price of share with their income per share. P/B is a ratio for comparing a markets value of stocks with its book value. A lower P/B ratio could mean that the stock is undervalued. On the other hand, it could entail that a particular aspect is fundamentally wrong with the company.

Z-score: The Z-score was developed by Altman (1968) and Altman and Hotchkiss (2010). It is a formula[(working capital/total assets)+1,4 (retained earnings/total assets)+3,3 (earnings before interest and taxes/total assets)+ 0,06 (market value of equity/book value of total debt)+ 1,0 (sales/total assets)]to measure firms financial wellbeing and forecast bankruptcy. Financial anguish is a driving force for fraud undertaken by management (Fanning & Cogger, 1998; Kinney et al., 1989; Loebbecke, 1989; Stice, 1991). As a ratio related to financial anguish, Altman's Z score was applied in this thesis, which developed to estimate financial distress. Many researchers use Zscore to forecast bankruptcy. These results of my research and the rate of correct classification have been analyzed below:

Table 12: Comparison of attributes and predictability

Attributes		**k-nn**	**NB**	**LR**	**SVM**	**DT**	**RF**	**LASS0**	**Total**
Total debt	(x_1)	✓							1
Log of total debt	(x_2)		✓	✓	✓			✓	4
Equity	(x_3)	✓		✓	✓				3
Debt to equity	(x_4)	✓			✓	✓	✓	✓	5
Total debt / total assets	(x_5)		✓		✓				2
Long term debt / total assets	(x_6)		✓					✓	2
Short term debt / total assets	(x_7)		✓		✓			✓	3
Account receivable/sales	(x_8)				✓			✓	2
Inventory/sales	(x_9)					✓		✓	2
Inventory / total assets	(x_{10})				✓	✓		✓	3
Sales growth	(x_{11})	✓					✓	✓	3
Sales	(x_{12})	✓							1
Gross margin	(x_{13})								0
Sales minus gross margin	(x_{14})	✓					✓		2
Total assets	(x_{15})		✓			✓			2
Log of total assets	(x_{16})			✓	✓		✓	✓	4
Net fixed assets/ total assets	(x_{17})		✓	✓	✓	✓	✓	✓	5
Gross profit/total assets	(x_{18})		✓		✓				2
Net profit/total assets	(x_{19})			✓				✓	2
Net profit/sales	(x_{20})							✓	1
Working capital	(x_{21})	✓							1
Working capital/total assets	(x_{22})								0
Sales to total assets	(x_{23})				✓		✓	✓	3
Current assets/ current liabilities	(x_{24})		✓						1
Net income/fixed assets	(x_{25})	✓			✓			✓	3
Cash/total assets	(x_{26})		✓	✓	✓			✓	4
Quick assets/current liabilities	(x_{27})								0
Earnings before interest and taxes	(x_{28})								0
Ebit /total assets	(x_{29})		✓	✓				✓	3
Equity/total liabilities	(x_{30})		✓					✓	2
Z-score	(x_{31})								0
Inventory	(x_{32})	✓							1
Net profit after tax	(x_{33})								0
Sector	(x_{34})	✓	✓		✓	✓	✓	✓	6
P/E	(x_{35})				✓				1
Price/book value	(x_{36})							✓	1
CVSR –ACCURACY		**89.11**	**68.29**	**69.50**	**78.13**	**80.80**	**85.30**	**69,62**	

The above table refers to the final performance for each attribute (vector) and different types of machine learning techniques. We estimate several machine learning techniques to conclude with the best combination. The choice of these ratios has the best CVSR for each attempt. Tables 35-40 in the appendix appear the best CVSR for each vector for each shot. We choose ensembles weights using five cross-validations.

As we referred to in Chapter 3, according to the theoretical framework proposed by Stolowy and Breton (2003), to understand data management accounting, the ratio of debt to equity is one of the fundamental ratios. This ratio explains the connection between assets and liability. According to the same theory, this ratio can also be reformed by increasing benefits or hiding money using engagement-generating strategies in balance. According to the results we derived from Table 12, we can conclude the importance of this ratio, as four of the six methods confirm the same result. All the selected ratios from our results are confirmed with prior studies.

A classification technique's selection for predicting FFS is a challenge, as making a suitable choice can significantly improve accuracy. This choice is not unique, as different classification methods can be incorporated, thereby enhancing the performance of the whole prediction of the fraudulent financial statement. In Table 12 in the bottom line, there appears the average success classification rate (CVSR – ACCURACY) for each method. In using the machine learning technique, numerous models with different performance features are available for use. As suggested by the'No Free Lunch Theorem', no learning algorithm is entirely best is present. Even the best models from our results are the K-nn (89, 11%), random forests (85, 3%) and decision trees (80.8%). On the other hand, SVM (78,13%), logistic regression (69.50%) ,NaiveBayes(68.29%) and Lasso (69.62%)have poor average performance.

5.3 Comparison of Prediction Performance

Evaluation of performance is utilised for judging the efficacy and measuring the performance of machine learning techniques.

Furthermore, K-fold cross-validation was applied for testing and training sets of a pre-processed dataset. A typical experiment uses K = 5. Stratified 5-fold cross-validations were used to divide samples into five-folds, with some figures of both fraud and fraudless cases. Each fold is to train classifiers and outline parameters; the remaining five-folds are for evaluating the sample's performance. Using test sets, this method calculates the usual accuracy of the classification of test sets. The six classifiers use the 5-fold cross-validation datasets (Table 12). The proposed ensemble of classifiers was authenticated based on the results of the classifiers.

Misclassification costs which are related to two error types, are also used in this study. Type I errors occurs when a fraudless case is categorised as a fraud case, while a type II error is committed when a fraud case is classified as a fraudless class. Error type II possesses a higher cost of the wrong classification than those related with type I errors (West, 2014). Incorrect decisions related to economic damage occur when a case of fraud is classified as a fraudless class; At the same time, additional investigation and expenses may result from categorising a fraudless case as fraud class.

Accuracy, sensitivity and specificity are the three most common standards of determining performance. Accuracy is the ration of effectively categorised samples to ineffective ones. Sensitivity (ratio of true positives to false positives) measure items acceptably classified as fraudulent to those wrongly listed as fraudulent. Specificity (true negatives with false negatives) occurs when the prediction is actually 'no' (Ravisankar et al., 2011). As mentioned previously, the core difficult of fraud detection is the large difference in the misclassification costs. A misdiagnosis of a fraudulent transaction that is genuine is more expensive than the opposite being the case. Moreover, we used misclassification rate, precision, null success rate and null error rate as the performance measures.

According to the literature results, this study concludes the CI method to possess a better rate of success compared to statistical methods. Random Forests and SVM show slightly better results than logistic regression with equivalent accuracy and specificity (Bhattacharyya et al., 2011). Also, the results of the literature showed large differences between each methods' sensitivity and specificity results. Bhattacharyya et al. (2011), in their research, showed that SVM, Random Forests and Logistic Regression were better at discovering genuine businesses properly than fraud ones. Also, Ravisankar et al. (2011) supported that Logistic Regression and SVM were slightly less sensitive.

The fundamental difficulty in identifying fraud lies in the massive difference in the wrong classification cost. A fake transaction is more costly when misdiagnosed and assumed to be genuine than the reverse case.

The 5-fold cross-validation performances of the seven classification methods were calculated and compared. The k-nn has the highest average accuracy (89,11%), followed by RF (85,30%) and DT (80.80%). NB has the lowest accuracy (68,29%). LR and SVM have accuracy rates of 69,50% and 78,13, respectively. Also, Lasso has a low average accuracy of 69.62%. The machine learning methods (RF, DT, k-NN and SVM) outperformed the statistical method (LR).

The confusion matrices for k-nn, LR, NB, SVM, DT, RF and Lasso are given below (Tables 13–19). Moreover, the performance matrix that indicates the sensitivity (type I error) and specificity (type II error) of the six methods used in this thesis are presented in Table 20. Sensitivity (type I error) and specificity (type II error) evaluate performance. The metric for sensitivity comprises correctly forecasted amount of fraudulent organisations to truly fraudulent organisations. The specificity of a model measures the number of fraudless firms predicted as fraudulent to non-fraudulent firms. Table 12 shows the average accuracies in all cases.

Table 13:Confusion Matrix for K-Nearest Neighbours (k-nn)

Observed	Predicted-Classified as k-nn	
	FFS	Non-FFS
FFS	1300 (correct classification)	113 (type II error)
Non-FFS	132 (type I error)	924 (correct classification)

Table 14:Confusion Matrix for Logistic Regression (LR)

Observed	Predicted-Classified as LR	
	FFS	Non-FFS
FFS	1250 (correct classification)	163 (type II error)
Non-FFS	590 (type I error)	466 (correct classification)

Table15:Confusion Matrix for Naive Bayes (NB)

Observed	Predicted-Classified as NB	
	FFS	Non-FFS
FFS	1299 (correct classification)	114 (type II error)
Non-FFS	669 (type I error)	387 (correct classification)

Table16:Confusion Matrix for Support Vector Machine (SVM)

Observed	Predicted-Classified as SVM	
	FFS	Non-FFS
FFS	1234 (correct classification)	179 (type II error)
Non-FFS	361 (type I error)	695 (correct classification)

Table 17:Confusion Matrix for Decision Tree (DT)

Observed	Predicted-Classified as DT	
	FFS	Non-FFS
FFS	1196 (correct classification)	217 (type II error)
Non-FFS	255 (type I error)	801 (correct classification)

Table 18:Confusion Matrix for Random Forests (RF)

Observed	Predicted-Classified as RF	
	FFS	Non-FFS
FFS	1267 (correct classification)	146(type II error)
Non-FFS	215 (type I error)	841 (correct classification)

Table 19:Confusion Matrix for Least absolute shrinkage and selection operator (Lasso)

Observed	Predicted-Classified as LASSO	
	FFS	Non-FFS
FFS	518.0 (correct classification)	538.0 (type II error)
Non-FFS	212.0 (type I error)	1201.0 (correct classification)

The results show that computational intelligence methods had better success rates than statistical methods (Table 20)—specificity shows slightly better results for k-nn and NB in comparison to LR and RF. DT and SVM have the lowest specificity. In addition, the error rate shows how often the methods yield wrong results. Table 20 shows that the lowest error rate is for k-nn followed by RF, DT, SVM, LR and NB. Precision shows how often a classifier is correct when it predicts fraud. The best results are for k-nn and RF.

Table 20: Sensitivity, specificity, accuracy, error rate, precision, null success rate and null error rate results

Sensitivity	Specificity	CVSR - Accuracy	Misclassification Rate- Error rate	Precision	Null success rate	Null error rate
K*- Nearest Neighbours *(k-nn)					57.23%	42.77%
87.50%	92.00%	89,11%	9.92%	89.10%		
Logistic Regression (LR)						
44.13%	88.46%	69,50%	30.50%	74.09%		
Naive Bayes (NB)						
36.65%	91.93%	68,29%	31.71%	77.25%		
Support Vector Machine (SVM)						
65.81%	87.33%	78,13%	21.87%	79.52%		
Decision Tree (DT)						
75.85%	84.64%	80,80%	19.12%	78.68%		
Random Forest (RF)						
79.64%	89.67%	85,30%	14.62%	85.21%		
Least absolute shrinkage and selection operator (Lasso)						
49.05%	84,99%	69,62%	30.37%	70.95%		

5.4 Conclusion

Improving stock performance, attempting to exaggerate performance following managerial pressure or reducing tax obligations, is the significant reason behind the companies' desire to participate in fraudulent financial statements (Ravisankar et al., 2011). Due to the irregularity with which it occurs, inadequate knowledge in the field and committed by well-informed and proficient persons at concealing their dubious act makes it difficult to diagnose financial statement fraud (Maes et al., 2002). Due to information asymmetry, the top management people have the advantages of having access to internal information and producing and concealing fraudulent accounting information. In essence, "wealth loss" caused by fraudulent financial reporting is also an inevitable cost of insider transactions in the principal-agent mechanism. Also, fraud comes into being only in an asymmetrical information situation. Therefore, fraudulent financial reporting does not record adverse selection and insider trading in an ineffective market (Forsythe et al., 1999). This study designed an improved framework to ascertain financial report fraud risks. The research focused on examining and identifying the ratos in finance linked to fraud detection in the financial report. This study also concentrated on studying and comparing the performance of seven classifiers (statistical and computational). Two of them are statistical methods (LR and NB), whereas five are machine learning techniques (DT, SVM, RF, k-nn and Lasso). Empirical results suggest machine learning techniques be the modest instrument for evaluating the risk of financial report fraud. Computational intelligence methods have shown better success rates compared with the statistical method. Empirical results obtained show the suggested classification method in the study can also help estimate the risk of FFS and decrease the financial risks of investors, economic analysts, auditors, governments, and banks. The rules and factors associated with critical financial factors are easily understandable, hence significant for audit decision-making.

Chapter 6: The Effect of the IFRS implementation on Earnings Management

6.1 Introduction

This thesis aims to investigate whether there is a more excellent quality of accounting by applying the IFRS. The companies listed in Greece are mandatory to adopt the IFRS in consolidated accounts' presentation and preparation for the period beginning from or after January 1, 2005 (Rule 1606/2002 of the European Commission). Until 2005, firms listed in Greece are mandated to apply the GAAP.

The objective of the published financial report is to provide info associated with the financial position. The changes in the firm's performance of the money situation would be vital in decision-making for investors, money lenders, goods suppliers, workers, customers, the government, and the general public.

The quality of financial reporting's has received great attention, mainly after the latest economic scandals referred to in Chapter 3. The concept of the term quality of accounting is yet challenging to define.

The IFRS is targeted at increasing for the public interest, a unique set of accounting standards of increased value that need transparent and comparable info in published financial reports. Conversely, no improved quality is presented by the IFRS.

6.2 Literature Review

6.2.1 IFRS and accounting quality

The IASC was established in 1973, and in 1975, the IASC published the first IFRS, and since then, the IFRS has undergone considerable evolution. In 2000, IOSCO recommended using IFRS by foreign-based issuers for cross border offerings (IOSCO, 2000). Following rule 1606/2002, the European Commission mandated financial reports to be prepared according to European public firms' IFRS. According to the IFRS

Foundation (2018), 166 countries have harmonised their accounting standards with IFRS.

Accounting quality can also be improved by limiting accounting techniques' flexibility, leading to decreased accounting flexibility use by unscrupulous management (Ashbaugh and Pincus, 2001). According to Bryce et al. (2015), stakeholders and investors require more transparent and accurate financial statements.

Later studies like Barth et al. (2008), Dimitropoulos (2013) and Christensen et al. (2015) investigate different accounting quality measures like timely loss recognition, value relevance and earnings management. In contrast, Chen et al. (2010) and Bryce et al. (2015) use accrual quality to measure the accounting quality. Fuad et al. (2018) use earnings persistence to extent accounting quality.

Previous researchers have associated the implementation of IFRS with the progress in accounting quality, but the results are contradictory. More specifically, according to the studies of Barth et al. (2008), Chen et al. (2010), Liu et al. (2011), Dimitropoulos et al. (2013) and Christensen et al. (2015), support that firms that adopt IFRS have higher quality information. They determine factors that reduce discretionary accruals and earnings management. In contrast, Ahmed et al. (2013), Bryce et al. (2015), Duarte et al. (2015) and Fuad et al. (2018) funding that accounting quality is not significant after the implementation of IFRS.

Also, some other researches, Callen et al. (2011) and Han et al. (2008) emphasise that accounting quality depends on national culture. Borker (2013) investigates that cultural factors are determinants of IFRS implementation. Furthemore, Alan (2018), Edeigba et al. (2019) and Anisah et al. (2020) support the role of cultural factors in accounting quality.

According to Anisah (2020), accounting quality is different in Emerging and Growth Leading Economies for many reasons. More specifically, the first reason is that the rate and the years of adopting IFRS are different among these countries. For example, according to IFRS- Foundation (2018), Indonesia, India and China adopted their national standards, which are substantially in line with IFRS. Still, they have not announced the programme for the full adoption of IFRS. D' Arcy et al. (2018) support that Emerging and Growth Leading Economies have different accounting quality as the adoption status is other overtime for the preparation of financial statements varies among these countries. According to Wijayana et al. (2018), one more object is the importance of cultural factors in accounting quality.

Also, Soderstrom and Sun (2007) found who analysed the special effects of IFRS adoption established that accounting quality's elements can be expressed in the usage of the worth of ethics, the country's judicial & political systems and enticements for financial reporting. Chen et al. (2010) assumed the suggestion that the association between accounting quality and IFRS implementation is not categorised to the economic significances' perception. Chand and Patel (2008) and Guerreiro, Rodrigues and Craig (2011) posited that the accounting systems influenced by the country's interpretation and adoption of the IFRS ethics are an economical, cultural, political & historic produced integrated into the beliefs of individuals.

Different incentives and economic environments of the firms associated with the financial reporting system accounts for these differences. Incentives for the firms sampled in our study may have influenced their choice of implementing the IFRS, causing it to change between the implementation periods. Companies may have adopted the IFRS for reasons that its local values might not have allowed them to reveal its quality of accounting and indicate their higher value of accounting quality, which are linked with greater accounting quality.

Concerning the financial environment, many companies implemented the IFRS, as they predicted that it might be a thing of compulsion in the future. The quality of accounting has improved globally (Land, 2002). All these reasons contribute to better accounting quality after the application of IFRS.

In contrast, Fuad et al. (2019), in their study, specify that there is no confirmation that the dimensions of accounting quality containing timely loss recognition, earnings smoothing and accrual quality improve IFRS convergence. More recent studies, like Basu et al. (2020), introduced the model of loan loss provisions. They show that linear regressions can be used to predict loan loss provisions. Also, net loan charges-off and loan loss provisions are associated positively with increases in non-performing loans and associated negatively with decreases in non-performing loans. Furthermore, they show that inferences change when the first-stage loan loss provision models incorporate asymmetry attributable to net loan charge-offs.

Although we may expect that the IFRS would have an association with greater accounting quality, as a minimum, two reasons behind why this might be false are present. The first reason is that the IFRS may have lower quality than domestic standards. This could happen if the administrative choice cannot eradicate the firms' capacity to accounting depths that are more insightful of a company's money standing and efficiency. There is also the possibility that the IFRS provides firms with better chances of managing their earnings, thus reducing accounting quality.

6.2.2 Quality of the IFRS and creative accounting in Greece

A lower degree of managing earnings is observed among businesses with an outsider, adequate shareholder protection, colossal stock market, ownership circulation (Leuz et al., 2003), with the most effective management of Greece and Australia's earning countries. Ding et al. (2007) study show that nonexistence enhances earnings management, with a very high absence score in Greece (Leuz et al. 2003).

With the IFRS' introduction, practices associated with creative accounting were estimated to be reduced. Greek GAAP permitted start-up costs' recognition as insubstantial assets. Therefore, it is apparent that firms in Greece advanced with start-up costs' excessive capitalisation. In a similar manner to unnecessary start-up cost capitalisation, firms tend to capitalise on research expenses, a relevant piece in Greece when high values of assets affect debt covenants, with banks being the chief providers of finance (Tzovas, 2006). Also, by not altering the study expenses and start-up cost, no profit reduction occurred in firms. This finding is consistent with Baralexis (2004) results, which established that to overstate profits, credit finance is the most vital firms motive. Research expenses and start-up cost implementation may negatively impact shareholders' equity as they do not meet IAS 38 criteria for recognition.

The choice of recognising liability of retirement pension was present in association with employees, as employee retirement in the year after permitted firms to report higher net incomes while not been explicit concerning the recognised liabilities. Because IAS 19 entails active in service employee's liabilities to be identified, its implementation is projected to provide a more precise picture of companies' pension liabilities and reduce net assets.

The Greek GAAP also permitted significant bias for recognising provisions. IAS 37 has better clear rules for provision recognition, thus impacting the net assets negatively. The adoption of IAS 39 also creates definite needs for evaluating receivables and loans. Because hedge accounting was not required in Greek GAAP, these differences impact the net assets negatively. While companies to affect market prices were allowed to recognise up to 10% of their shares as assets, the IAS 32 requirements were anticipated to reduce net assets for decreasing woned percentage from shareholders' equity.

IAS 36 requires companies to 'assess for any indication of an impaired asset. With such signals, companies may estimate the recoverable amount of the asset as standards are set to provide clear rules & regulations for assessing impairment of assets and recoverable amount valuation. The GAAP in Greece was less explicit in this regard causing Greek companies in many instances not to identify asset impairments. The last in, first-out (LIFO) means is not allowed by the IAS 2, commonly used under the Greek GAAP to measure inventories' cost. It also clearly requires firms to cost inventories at a lesser price and recognise any impairment. Any observed deviations in inventories value were expected to be revealed. IAS 18 provided different requirements for sold goods returns recognition, reducing current asset value, thus negatively impacting net assets.

6.3 Measures of Accounting Quality

Quality accounting is assessed via the management of earnings and prompt loss recognition measures to previous studies. We studied two comportments of earnings management. The first compartment contains earnings smoothing, and the second comportment entails the management of positive earnings. We are predictable that the IFRS earnings would be less managed than the Greek GAAP, as the IFRS limits organisations' choices to present their earnings, which shows the firm's lower financial performance. According to studies, applying the Greek GAAP firms with lesser earnings levelling shows more unpredictability of earnings (Raedy & Yetman, 2003; Leuz *et al.*, 2003; Ball & Shivakumar, 2005, 2006; Lan et al., 2006). It is presumed in this study that companies that implemented the IFRS possess more flexible earnings. Several studies support our expectation.

Levelling of earnings is less distinct among countries practising common law (Leuz et al., 2003), which also have a similar conceptual framework of the IAS/IFRS. The application of accounting standards restricts an organisation's choice resulting in greater inconsistent accounting earnings (Ewert & Wagenhofer, 2005). Studies proposed prompt acknowledgement of profit & loss consistent with increased quality of earnings may raise instability of earnings with the flow of money (Ball & Shivakumar, 2005,2006). Two measure of the inconsistency of earnings was used in this study to study our anticipation. While the first metric consists of inconsistency in net income, the second metric is unevenness in net income than the change in cash flow's imbalance.

In this study, it is anticipated that applying the IFRS would affect companies that having fewer earnings management with subsequent higher earnings variability. To produce higher earnings unevenness, managers might utilise freedom of choice (Healy, 1985). Therefore, firms implementing local ethics demonstrate greater freedom of choice for managing earnings, resulting in more significant earnings unevenness. Moreover, due to the errors made in estimating accruals, lower earnings quality could indicate higher earnings variability, while higher quality accounting can lead to lower earnings variability.

The researches also reported a negative correlation as an indicator of levelling earnings, where executives increase accruals as a reaction to insufficient flow of money(Lang et al., 2003; Leuz et al., 2003; Ball & Shivakumar, 2005, 2006; Lang et al., 2006). Therefore, it is presumed that companies with increased earnings volatility present a more negative association between the cash flow and accruals. Ball & Shivakumar (2005, 2006) showed that prompt recognition of profit and loss reduces the negative relation between cash flow and the accruals. Consequently, we can forecast firms that adopt the IFRS to show a fewer negative correlation between accruals and cash flows than firms that use domestic standards.

Although this study predicted more outstanding accounting quality could cause the reduced negative association between the cash flow and accruals.

Dechow (1994) suggested that a negative correlation exists between cash flow and accruals, where accruals role in the assessment of income is for unevenness of cash flow. Thus, companies that adopt domestic standards can fare with their earnings to show the reduced undesirable relation between accruals and cash flow. Reduced undesirable association between accruals and cash flow may indicate reduced accounting quality, resulting from errors made in estimating accruals. In contrast, the increased undesirable association between cash flow and accruals can result in more outstanding accounting quality.

Prior studies with small positive net income are a measure for providing positive earnings (Burgstahler & Dichev, 1997; Leuz et al., 2003). This measure shows how organisations favour reporting only their positive net income. Therefore, this study predicted that the companies that adopt the IFRS report their small positive income compared with organisations that use local ethics, expecting that more outstanding quality of earnings would show increased incidence for huge losses regarding rapid recognition of loss. Ball et al. (2000), Lang et al. (2003), Leuz et al. (2003), Ball and Shivakumar (2005, 2006), and Lang et al. (2006) reported negative correlation as an indicator of earnings smoothing, where managers increase accruals in responding to poor cash flow outcomes.

Although this study predicted more outstanding quality of accounting leads to a greater incidence of losses. Also, Big bath management of earnings can be indicated by significant losses with a higher. Moreover, great losses with a higher frequency can also result from errors in the act of assessing accruals. Consequently, more outstanding accounting quality could lead to a lesser incidence of more significant losses.

6.4 Research Design

6.4.1 Accounting quality metrics

6.4.1.1. Earnings management.

This study utilises four measures for managing earnings; three for levelling earnings and one for earnings management. The first means for balancing earnings is inconsistency in net income evaluated by total assets (Barth et al., 2005; Lang et al., 2006; Leuz et al., 2003). We considered the higher variance in the net income change as evidence of earnings smoothing occurring at a lower level. Changes in the net income are likely sensitive to different factors that can not be ascribed to the financial reporting system. Thus, studies by Lang et al. (2006) & Raedy & Yetman (2003) regards the inconsistency in earnings as a residual change from the worsening of the net income (ΔNI) acting as control factors (Pagano, Röell & Zechner, 2002; Tarca, 2005), ΔNI.

$$\Delta NI_{it} = \alpha_0 + \alpha_1 SIZE_{it} + \alpha_2 GROWTH_{it} + \alpha_3 LEV_{it} + \alpha_4 DISSUE_{it} + \alpha_5 TURN_{it} + \alpha_6 CF_{it} + \alpha_7 AUD_{it} + \varepsilon_{it} \quad (24)$$

where SIZE= the natural log of the end-of-year market value of equity

GROWTH = percentage change in sales

LEV =end-of-year total liabilities divided by end-of-year equity book value

TURN = sales divided by end-of-year total assets

DISSUE = percentage change in total liabilities

CF = annual net cash flow produced by operating activities

AUD =an indicator variable that equals 1 if the firm's auditor is PwC, KPMG–Deloitte, Grant Thornton, E&Y, and 0 otherwise.

Our second levelling of earnings deals with the ratio of the inconsistency of net income (ΔNI) to the inconsistency of the functional flow of money (ΔC). In cash accruals are used by firms to cope with their incomes, inconsistency in the net income would be lesser than the same in operating cash flows. The companies that show more volatile cash flows typically have net income that is more volatile. Consequently, our second metric tries to act as a control for this. Just like ΔNI, ΔCF can be sensitive towards variegated factors that cannot be attributed to the financial reporting system. Consequently, the following equation (25) was also calculated by us with ΔCF as the dependent variable:

$$\Delta CF_{it} = \alpha_0 + \alpha_1 SIZE_{it} + \alpha_2 GROWTH_{it} + \alpha_3 LEV_{it} + a_4 DISSUE_{it} + \alpha_5 TURN_{it} + \alpha_6 CF_{it} + \alpha_7 AUD_{it} + \varepsilon_{it} \quad (25)$$

Our third earning levelling measure relies on the association between cash flow and accruals. We can adopt, Eqs. (24) and (25) are variability metrics from which we can associate with residuals from Eqs. (26) and (27), rather than directly comparing the association between ACC and CF. As with Eq. (24) and (25), the control variables are regressed on ACC; the following can be obtained

$$CF_{it} = \alpha_0 + \alpha_1 SIZE_{it} + \alpha_2 GROWTH_{it} + \alpha_3 LEV_{it} + a_4 DISSUE_{it} + \alpha_5 TURN_{it} + \alpha_6 AUD_{it} + \varepsilon_{it} \quad (26)$$

$$ACC_{it} = \alpha_0 + \alpha_1 SIZE_{it} + \alpha_2 GROWTH_{it} + \alpha_3 LEV_{it} + a_4 DISSUE_{it} + \alpha_5 TURN_{it} + \alpha_6 AUD_{it} + \varepsilon_{it} \quad (27)$$

In the end, we examined if firms manage their earnings towards achieving small positive earnings (Barth et al., 2005; Burgstahler & Dichev, 1997; Leuz et al., 2003). The coefficient on the SPOS in the regression is given by Eq. (25). When associating IAS and Non-International Accounting Standards (NIAS) companies in the pre-adoption period, we estimated pooling observations from the pre-adoption period as given in Eq. (28).

$$IAS(0,1)_{it} = \alpha_0 + \alpha_1 SPOS_{it} + \alpha_2 SIZE_{it} + \alpha_3 GROWTH_{it} + \alpha_4 LEV_{it} + a_5 DISSUE_{it} + \alpha_6 TURN_{it} + \alpha_7 CF_{it} + \alpha_8 AUD_{it} + \varepsilon_{it} \quad (28)$$

where is IAS(0,1) = an indicator variable that equals 1 for IAS companies and 0 for NIAS companies, and

SPOS= an indicator variable that equals one if the net income scaled by total assets is between 0 and 0.01 (Lang et al., 2003). With a negative SPOS coefficient, NIAS firms fare with earnings of small quantities than IAS firms.

Our inference is centred on the coefficient obtained on SPOS. (28) instead of comparing directly the percentages of small positive income of firms using IAS and NIAS, because *SPOS* coefficient reflects controls' effects of the factors that can be attributed to the financial reporting system.

6.4.1.2. Timely loss recognition

This study measures prompt recognition of a loss on large negative net income using the regression Eq.(29) (Lang et al., 2003; Lang et al., 2006). Comparing firms utilizing IAS and NIAS in pre-adoption period, we estimated. (29) by pooling observations from the pre-adoption period as follows:

$$IAS(0{,}1)_{it} = \alpha_0 + \alpha_1 LNEG_{it} + \alpha_2 SIZE_{it} + \alpha_3\, GROWTH_{it} + \alpha_4 LEV_{it} + \alpha_5\, DISSUE_{it} + \alpha_6 TURN_{it} + \alpha_7 CF_{it} + \alpha_8 AUD_{it} + \varepsilon_{it} \quad (29)$$

LNEG= an indicator variable that equals 1 for observations for which annual net income scaled by the total assets is less than -0.20, and 0 otherwise. LNEG positive coefficient specifies IAS firms to acknowledge huge losses than NIAS firms.

The LNEG coefficient from Eq. (29) was used in this study to evaluate if IAS were less probable in managing earnings.

6.5 Conclusion

In this chapter, we conduct a literature review on the IFRS. Specifically, we refer to the definition of accounting quality. Second, we present to the IFRS and accounting quality; third, we present to the quality of IFRS in Greece and fourth, we refer to the definition of earnings quality and its measures.

Chapter 7 Emprimental Result

7.1 Sample

Our sample is the same as the one described in Chapter 4. Our sample comprises data from 231 companies that were listed in the ASE between 2002 and 2015. We studied the number of companies per industry in Table 10b given in Section 4.11 without the companies involved in financial services, utilities, and banking, from the sample. The period between 2002 to 2004 is the implementation of the Greek GAAP period and from 2005 to 2015 as the IFRS implementation period. Our sample comprised only data from Greece without a corresponding sample technique, like studies by Barth et al. (2005).

7.2 Hypothesis– Results of the Comparison between IFRS and domestic standards

The fourth research question entailed comparing the accounting quality (earnings quality and timely loss recognition) of the companies listed in Greece before the implementation of the IFRS.

This study investigated whether the value of earnings was raised when IFRS was implemented. Thus, this study forecast was linked to the levelling of earnings. As a code law country (Greece), this study anticipated that earnings levelling was more prominent with firms implementing domestic ethics than IFRS executing firms. Leuz et al. (2003) showed that the level of earnings is far apparent among countries not practising common law. This led to our assumption being formed as follows:

H0: We expected that there was no significant changes before and after the implementation of IFRS.

Our leading metric is related to the prediction of the value of earnings. This study forecasted the levelling of earning to be more prominent before adopting the IFRS standard. Our hypothesis, checked with the comparison of inconsistency in net income as evaluated by the total assets (Barth et al., 2005; Lang et al., 2006; Leuz et al., 2003) before and after adopting the IFRS. The outcomes are shown in Table 21 given below.

Table 21: Net Income Variability

	DOMESTIC COMPANIES	IFRS COMPANIES
Variability	0.320	0.9777
Number of Observations	390	1406

Table 21 presented that the companies that implemented the IFRS show considerably greater inconsistency in the net income changes. The variability is 0.320 with Greek GAAP against 0.9777 with the IFRS. This outcome suggests that companies published less smooth earnings for the period when they implemented IFRS than when they implemented Greek GAAP standards.

This study levelling of earning measurement relies on the ratio of inconsistency in net income to inconsistency in functional cash flow. This study calculated the variability from Eq.25. The outcomes are shown in Table 22 given below.

Table 22: Cash Flows and Net Income Variability from Operations

	DOMESTIC GAAP COMPANIES	IFRS COMPANIES
Variability	191.861	396.714
Number of Observations	390	1406

Table 22 presents that the ratio of the inconsistency of net income to the inconsistency of cash flow from operations is greater for the period of IFRS implementation than for the period when the domestic GAAP was implemented. This result agrees with the fact that the implementation of IFRS generates less net income as the unpredictability of cash flow is not the only contributing factor.

The third levelling of earnings measurement relies on the association between accruals and cash flow (Eqs.26 and27). Tables 23 to 26 presents findings using Spearman correlation before and after the implementation of the IFRS regarding cash flow and accruals.

PANEL A

Table 23: Spearman correlation between ACC and CF <u>before</u> the implementation of the IFRS (Eq. 23)

	SIZE	GROWTH	LEV	DISSUE	TURN	AUD	SECTOR	CF
SIZE	1	0.144052	0.015767	-0.11659	0.065025	0.140961	0.040884	0.5771
GROWTH	0.144052	1	0.130104	-0.41546	0.279204	0.080534	0.024451	0.28217
LEV	0.015767	0.130104	1	-0.11253	0.333699	0.169966	-0.0298	0.015958
DISSUE	-0.11659	-0.41546	-0.11253	1	-0.01537	0.008405	0.038718	-0.15307
TURN	0.065025	0.279204	0.333699	-0.01537	1	0.197891	-0.07821	0.141103
AUD	0.140961	0.080534	0.169966	0.008405	0.197891	1	-0.18291	-0.00126
SECTOR	0.040884	0.024451	-0.0298	0.038718	-0.07821	-0.18291	1	0.021335
CF	0.5771	0.28217	0.015958	-0.15307	0.141103	-0.00126	0.021335	1

Table 24:Spearman correlation between ACC and CF <u>after</u> the implementation of the IFRS (Eq 23)

	SIZE	GROWTH	LEV	DISSUE	TURN	AUD	SECTOR	CF
SIZE	1	0.413481	0.032795	-0.22099	0.148574	0.290119	0.032971	0.550377
GROWTH	0.413481	1	0.242797	-0.46153	0.524663	0.159822	0.098463	0.406127
LEV	0.032795	0.242797	1	-0.23112	0.295424	0.045992	-0.02756	0.147023
DISSUE	-0.22099	-0.46153	-0.23112	1	-0.02521	-0.09756	0.009373	-0.25716
TURN	0.148574	0.524663	0.295424	-0.02521	1	0.131341	-0.03013	0.273088
AUD	0.290119	0.159822	0.045992	-0.09756	0.131341	1	-0.11035	0.212309
SECTOR	0.032971	0.098463	-0.02756	0.009373	-0.03013	-0.11035	1	-0.06095
CF	0.550377	0.406127	0.147023	-0.25716	0.273088	0.212309	-0.06095	1

PANEL B

Table 25: Spearman correlation between ACC and CF <u>before</u> the implementation of the IFRS (Eq 24)

	SIZE	GROWTH	LEV	DISSUE	TURN	AUD	SECTOR	ACC
SIZE	1	0.153336	0.008544	-0.11616	0.07669	0.128423	0.031285	0.013339
GROWTH	0.153336	1	0.132542	-0.42099	0.294588	0.082985	0.017989	0.107033
LEV	0.008544	0.132542	1	-0.11235	0.343824	0.160908	-0.03174	0.045353
DISSUE	-0.11616	-0.42099	-0.11235	1	-0.0296	-0.01366	0.038398	-0.09678
TURN	0.07669	0.294588	0.343824	-0.0296	1	0.169577	-0.08441	0.129744
AUD	0.128423	0.082985	0.160908	-0.01366	0.169577	1	-0.17412	0.172546
SECTOR	0.031285	0.017989	-0.03174	0.038398	-0.08441	-0.17412	1	-0.00771
ACC	0.013339	0.107033	0.045353	-0.09678	0.129744	0.172546	-0.00771	1

Table 26:Spearman correlation between ACC and CF after the implementation of the IFRS (Eq 24)

	SIZE	GROWTH	LEV	DISSUE	TURN	AUD	SECTOR	ACC
SIZE	1	0.389203	0.026656	-0.17478	0.160336	0.276873	0.013165	0.150094
GROWTH	0.389203	1	0.24941	-0.42583	0.50831	0.153461	0.061162	0.125016
LEV	0.026656	0.24941	1	-0.23878	0.302746	0.054748	-0.02249	-0.09255
DISSUE	-0.17478	-0.42583	-0.23878	1	-0.04845	-0.11612	0.024049	0.156298
TURN	0.160336	0.50831	0.302746	-0.04845	1	0.140485	-0.04888	0.183709
AUD	0.276873	0.153461	0.054748	-0.11612	0.140485	1	-0.12563	-0.06339
SECTOR	0.013165	0.061162	-0.02249	0.024049	-0.04888	-0.12563	1	0.035595
ACC	0.150094	0.125016	-0.09255	0.156298	0.183709	-0.06339	0.035595	1

Tables 23-26 indicate the correlation matrix by Spearman. The correlation matrix above shows the correlation coefficient between cash flow and accruals before and after adopting IFRS. Most variables like GROWTH, LEV TURN, AUD, SECTOR, and CF indicate a positively correlated. Only the variable of DISSUE indicates a negative linear correlation. This result suggests that accruals and cash flow are associated to all the variables of the equation. One significant impact is that the values of coefficients increased after adopting IFRS, which means that LEV, GROWTH, TURN, SECTOR, AUD, CF and DISSUE are strongly related to accruals and cash flow.

The last metric for earnings managing was estimated with Eq.28. We tested if firms manage earnings to small earnings that are positive—coefficient of small positive net income on SPOS is presented in Eq. 28. We calculated the Logit model to compute the SPOS coefficients.

Table 27: Logit model for variable SPOS

No. Observations:	1801	Model:	Logit
Df Residuals:	1791	Method:	MLE
Df Model:	9	Pseudo R-squ.:	0.2037
Log-Likelihood:	-749.35	converged:	TRUE
LL-Null:	-941.03	LLR p-value:	4.86E-77

	coef	std err	z	P>|z|	[0.025	0.975]
const	9.9937	0.862	11.588	0.000	8.303	11.684
SIZE	-1.3021	0.119	-10.963	0.000	-1.535	-1.069
GROWTH	0.037	0.078	0.474	0.635	-0.116	0.19
LEV	-3.74E-05	0.004	-0.008	0.993	-0.009	0.009
DISSUE	-0.7985	0.077	-10.407	0.000	-0.949	-0.648
TURN	-0.1076	0.083	-1.304	0.192	-0.269	0.054
CF	1.21E-08	3.87E-09	3.124	0.002	4.50E-09	1.97E-08
AUD	0.7682	0.161	4.772	0.000	0.453	1.084
SPOS	-0.5161	0.153	-3.37	0.001	-0.816	-0.216
SECTOR	0.0322	0.018	1.768	0.077	-0.003	0.068

The SPOS coefficient is negative and statistically significant, implying NIAS firms can manage their earnings than IAS firms. R^2 is 0.2037 and is relatively low, but we can interpret this fact as our sample values are low. Also, variables of Dissue (percentage change in total liabilities), Size, AUD(Audit), and CF (Cash Flow) are statistically significant according to the p-value. The importance of variables of CF, Dissue, and Size are known. Consistent with De Angelo (1981), the audit firm's size is an essential criterion for undertaking quality control. Many other researchers, like Balvers et al. (1988), Beatty (1989), Craswell et al. (1995), DeFond et al. (2000), Dye (1993), Gaganis and Pasiouras (2006), Ireland and Lennox (2002), Keasey et al. (1988), Menon and Williams (1991), Pong and Whittington (1994), consistent with the argument of De Angelo referred that the bigger sized audit companies (such as PricewaterhouseCoopers, Deloitte, KPMG and Ernst and Young) with international reputation provide reports that demonstrate a higher degree of precision and record indications, such as financial failure (Lennox, 1999; Petroni &Beasley, 1996) and disputes (Palmrose, 1998). Consequently, the bigger audit companies find it more difficult to recede from the pressure of the firms (Krishnan &Schauer, 2000), as they want to protect their reputation. Moreover, they have more experience in different firms' industries and can have access to more data (Benston, 1980).

Also, Titman and Trueman (1986) and Datar et al. (1991) referred that welfare companies prefer to be controlled by bigger audit companies, as they demonstrate more effective audit control. The researches shown by Deis and Giroux (1992) and Colbert and Murray (1998) mentioned a strong correlation between the size of the audit company and its control quality. In contrast , some researchers support no correlation between the audit firm's size and its control quality.

Also, the sample was tested for endogeneity, heteroscedasticity, and multicollinearity. The possibility of different independent variables relating to one another can occur. In case the independent variables are correlated, it is impossible to correctly estimate the variables' beta coefficients (Gujarati, 2003). The presence of multicollinearity makes it challenging to identify the distinct effects of independent variables. Consequently, some variables should be excluded as the independent variable's effects on the dependent variable cannot be determined. The variance inflation factor (VIF) shows how independent variables relate to other independent variables used to test multicollinearity. Collinearity occurs when two independent variables are related. For no multicollinearity to occur within different variables, the VIF value should be ≤10 (Guajarati, 2003). No multicollinearity happened in the sample (Table 52) because VIF values are ≤10. Also, heteroscedasticity was checked with the Breusch–Pagan test.

The last but not least, we checked the sample for endogeneity. We followed three steps to check the endogeneity. Firstly, we completed endogeneity tests the null hypothesis has exogenous variables (H0: variables are exogenous). We rejected the null hypothesis if the p-value was low. Secondly, we testified the first-stage regression to check if the instruments are weak. We applied the Partial R^2 to check if there is a correlation between the instruments and endogenous variables. We rejected the null hypothesis whether the F-statistic is the largest from the critical value. The final step to check the endogeneity entails performing tests for overidentifying restriction with Sargan and Basmann tests. The H0 established the validity of the instruments and mentioned that the model is correctly specified. Moreover, the results appear in Table 53 of the Appendix. Consequently, it should conclude that the sample does not demonstrate endogeneity.

Furthermore, we evaluated prompt recognition of loss as the coefficient of LNEG presented in Eq. 29. We also calculated the Logit model to evaluate the coefficients of LNEG.

Table 28 Logit model for variable LNEG

No. Observations:	1800	Model:	Logit
Df Residuals:	1790	Method:	MLE
Df Model:	9	Pseudo R-squ.:	0.2077
Log-Likelihood:	-745.38	converged:	TRUE
LL-Null:	-940.78	LLR p-value:	1.249e-78

	coef	std err	z	P>|z|	[0.025	0.975]
const	9.2914	0.868	10.704	0.000	7.590	10.993
SIZE	-1.2298	0.120	-10.280	0.000	-1.464	-0.995
GROWTH	0.0596	0.084	0.710	0.478	-0.105	0.224
LEV	-0.0007	0.004	-0.176	0.860	-0.009	0.007
DISSUE	-0.8065	0.078	-10.299	0.000	-0.960	-0.653
TURN	-0.1087	0.085	-1.286	0.198	-0.274	0.057
CF	1.261e-08	3.94e-09	3.199	0.001	4.88e-09	2.03e-08
AUD	0.7726	0.161	4.795	0.000	0.457	1.088
LNEG	1.521	0.417	3.645	0.000	0.703	2.339
SECTOR	0.028	0.018	1.552	0.121	-0.007	0.064

The LNEG coefficient is positive and statistically significant. Positive LNEG coefficient implies firms that implemented the IFRS recognise large losses more frequently in the post-adoption than in the pre-adoption period. In this equation, the R^2 is 0.2077 and is relatively low, but we can interpret it as our sample values are low. Furthermore, variables of Dissue (percentage change in total liabilities), Size, AUD (Audit), and CF (Cash Flow), as given in the previous equation, are statistically significant according to the p-value. Also, the sample was tested for multicollinearity, heteroscedasticity and endogeneity. Also, multicollinearity was checked with VIF, heteroscedasticity was checked with Breusch–Pagan test and endogeneity was checked, as described above. Moreover, the results appear in Tables 54, 55 and 56 given in the appendix. Therefore, it can conclude that the sample does not have multicollinearity and endogeneity.

7.3 Conclusions of the Research

Our results report that the firm that applied IFRS possesses a higher value of accounting than other firms that do not. Comparing the Greek's financial accounting system with the quantities of accounting in this study, we observed that companies that applied the IFRS demonstrated less earning levelling and reduced earnings management with rapid losses recognition.

Also, this chapter shows the relation with dealing with implementing the IFRS and management of earnings of the firm. This study used figures obtained from companies located in Greece. It is argued that the adoption of standards with good quality could be an essential aspect for the realisation of first-class information (Ball *et al.,* 2003). Leuz et al. (2003) hypothesised that the IFRS' adoption would reduce Greece earnings management and classifying Greece as displaying one of the greatest managers of earnings.

This study also established huge prospects in Greece earnings management, making Greece a remarkable study area investigating whether the IFRS' adoption affected the utilisation of enhanced accounting quality and creative accounting.

Various approaches have been applied to examine the occurrence of levelled earnings in companies in prior research. This leads to three categories of literature based on research designs utilised in earnings management: literature targeting particular accruals, cumulative accruals and those circulated after proper management of earnings.

Four different means of managing earnings (involving three means of earning levelling and a means for managing earnings) have been used in this study. Firstly we measure levelling earnings is based on net income's unpredictability (Barth et al., 2005; Lang et al., 2006; Leuz et al., 2003). A higher change variance in net income is evidence of the lower level of earnings smoothing. Changes in net income may be sensitive to various factors that cannot be attributed to the structure of reporting finances, like the financial atmosphere and motivations to adopt IFRS. Secondly we measure levelling earnings is by the proportion of net income's unpredictability (ΔNI) to the unpredictability of the operational flow of cash (ΔC). Organisations with greater unstable cash flow usually possess higher inconsistent net income; an observation of the second parameter in this study acts as a control. Thirdly we measure earnings levelling means in this study between accruals and the cashflow using Spearman correlation. Finally, this study tested if firms manage earnings towards achieving small positive earnings (Barth et al., 2005; Burgstahler & Dichev, 1997; Leuz et al., 2003). This study also measured timely loss recognition as a coefficient on large negative net income, LNEG (Lang et al., 2003; Lang et al., 2006).

The present study used a dataset consisting of 231 Greek companies listed on the ASE between 2002 and 2015 and compared accounting quality metrics for companies before and after adopting the IFRS. Findings from the present study indicate that the IFRS firms have higher accounting quality. Even if diverse motivations for managing earnings were considered using control variables, other incentives might not be included in the model, limiting this study. Second, this study also finds managing earning as a means of assessing the earnings quality.

Chapter 8: Conclusions

8.1 Introduction

The desire to improve the value of stocks, decrease tax responsibilities, or inflate a firm's performance due to pressure from management is ample motives for FFS (Ravisankar et al., 2011). FFS is not frequent and perpetrated by professionals in the field, hence difficult to detect (Maes et al., 2002). This study designed an improved framework system of financial risk factors for evaluating the risks of financial statement fraud. The present study concentrated on examining and identifying the financial ratios that are linked to uncovering fraud in financial statements and comparing the performance of seven classifiers (statistical and computational) and involves two statistical methods (LR and NB) and five machine learning techniques (DT, SVM, RF k-nn and lasso).

This study also examined whether the IFRS's implementation is linked to the more outstanding quality of accounting. To verify the preparation and demonstration of merged accounts by January 1, 2005, Greece firms listed were required to adopt the IFRS (Rule 1606/2002 of the European Commission). They were obligated to implement local ethics (GAAP) until the due period.

8.2 Objectives and Questions of the research

8.2.1 Research objectives

This survey has two main aims. The first aim investigates the first three research questions. Precisely, the first objective of the study ascertains financial ratios that are linked to FFS. We also attempted to verify the ability of the financial ratio to forecast FFS. We compared various data mining methods, including DT, NB, LR, RF,k-nn, SVM and Lasso. Thus, the first objective is to construct a comprehensive classification framework to apply machine learning methos in fraudulent financial statements detection.

The second object of this thesis is to examine if IFRS is connected with a more outstanding quality of accounting.

8.2.2 Research questions

The aims of this research answered the following questions:

Q1: Which financial ratios are linked to the detection of fraud in financial reports?

Q2: What is the predictive power of the financial ratio on fraud in financial reports?

Q3: Can a computational intelligence framework be used for the avoidance and unmasking fraud in financial reports?

Q4: Are financial reports in Greece reliable? Have there been any changes regarding the quality of accounting post-implementation of the IFRS in Greece?

8.3 Findings of the research

8.3.1 Financial ratios associated with the detection of FFS

In a capitalist economy, bond markets and stocks are essential components. The flexibility, effectiveness and liquidity of these components depend on evaluating the financial capability of capital raising businesses. The success of the capital market is also determined by the published financial statements prepared by such firms. These published financial statements unveil vital info on a company's past, present, and prospect. It presents a fair financial status of the company because it is with integrity they were prepared.

Specific questions were asked and include; are there any essential ratios for detecting FFS? Which of the ratios can reflect financial statement fraud? Can the proportion finance model support fraud detection? Responses to these questions can provide assistance to decide the best choice of ratio to adopt. Even if models are equally correct in detecting fraudulent firms, suspicious-looking firms are not fraudulent after investigation.

In our research study, Table 12 in Chapter 5 presents different methods for fraud factors and compares data results. Also, Table 12 shows the significant factors that are comprised of the estimated models. The main kind of detection of fraud is 'poor performance'. Leverage proxies(long term debt/total assets, total debt, total debt/total assets, the logarithm of total debt, short-term debt/total assets and debt to equity) reflect a major result assign for fraud investigation. Consistent with Fanning and Cogger (1998), Kirkos et al. (2007), and Ravisankar et al. (2011), the probability of the FFS increases when levels of debt are higher. However, Persons (1995) claimed that if a high debt ratio is linked with fraudulent financial statements is an open question. Financial fraud's likelihood is amplified by a high debt structure, as the risk from the managers and equity owners to the debt owners is shifted by the latter. Managers may manipulate financial statements as a result of the requirement to come across to their debt covenants. This presents that increased levels of debt should growth the possibility of fraudulent financial statements. It also entails that the companies with a high TD/TE rate demonstrate an amplified likelihood of being categorised as fraudulent. As mentioned in Section 1.2.1, Holthausen and Leftwich (1983), Persons (1995), Watts and Zimmerman (1990) and Christie (1990) argued that high debt structure is a likely motivator of FFS. Moreover, Loebbecke et al. (1989) established that 19% of companies in their model display creditworthiness problems.

Unliquidity should be a motivation for chiefs to take part in FFS, a statement corroborated by the studies of Kreutzfeldt and Wallace (1986), who reported that companies that suffer liquidness exhibit further faults in their published financial statements. Liquidity ratios have been examined by the researchers Lenard and Alam (2009) and Ravisankar et al. (2011), and Spathis (2002).

Furthermore, lower profits may give incentive to the firms' management to understate expenses or overstate revenue. This approach has its basis as the expectation that the management can increase past profitability levels (Summers et al. 1998). However, whether this assumption is not satisfied by presentation performance, then it would motivate FFS. Financial distress is a motivator for FFS (Kreutzfeldt &Wallace, 1986; Loebbecke et al., 1989). In this study, the best significant profitability ratios for fraudulent financial statements are:

- Gross profit to total assets.
- Net profit to total assets.
- Net income to fixed assets and EBIT to total assets.

Fraudulent misrepresentation is common in accounts such as sales, inventory and receivables that authorise personal assessment, as they are more challenging to audit because they can be manipulated (Stice, 1991; Feroz et al., 1991; Persons, 1995). Fraud can also be committed when sales are recorded as earned (Fanning & Cogger, 1998), with 14% and 225 of FFS for receivable accounts and inventory (Loebbeck et al., 1989).

An organisation's management may influence records by recording outdated records and records at a lesser cost (Stice, 1991; Persons, 1995). More so, personal assessment of financial report occurs in forms and receivable accounts (Kirkos et al., 2007; Perols, 2011), thus making records, sales, receivable accounts to sale ratio, records to sale ratio, sales growth and sales to asset ratio are the essential ratios for unmasking fraudulent financial reports.

To increase net income to reinforce its balance sheet, a firm's sales and costs of good sold may be unequal/ (Fanning & Cogger, 1998).

The result from the present study confirms the significant ratio of sales minus gross margin (Fanning and Cogger, 1998).

Furthermore, ratios of structure, such as inventory to total assets,

the log of total assets, total assets, equity to total liabilities, net fixed assets to total assets and equity, are significant. We also examined the investment ratios. According to our results, the price-earnings ratio is substantial.

8.3.2 Financial ratios predictability on FFS

The question raised is how an investor possessing the stock should act if a company declares a significant and doubtful accounting misstatement and, as a consequence, the stock price falls. Are ratios able to assist in predicting which fraud companies will outlive? This query is hard to answer because surveys have to conclude when to take into account the loss of reputation of the firm that took part in accounting misstatement. We have emphasised the study which utilised financial statement fraud examples and concluded that much proof is not available for answering this question. Consequently, it seems that making authority alterations may increase the possibility of a company's outlive (however, this does not always mean that it will also regain its flawed fame). Nevertheless, numerous fraud companies go solvent after three years of the statement, making the low quality of accounting a helpful forecaster of economic suffering and bankruptcy.

The next question that arises is which financial ratios play an essential role in forecasting fraud. According to the survey, fraud companies seem to be development companies that need cash. As a result, massive accruals, trade development, receivables development, lease inventory development and so on suggest possible misstatements. Fraud companies are inclined to possess a high ratio of market sales and recorded sales. Greater previous stock earnings than bankruptcy in scaling down model in that the ratio of market sale and recorded sales are low or unimportant incomes generated from stock are negative.

There are many aspects that affect the numbers that appear in the financial statements. Nevertheless, only some of them will play an essential role in the models that forecast financial statement fraud. Our study concentrates only on models which predict financial statement fraud.

8.3.3 Can a computational intelligence framework be used for the prevention and detection of FFS'S?

Our research directs its attention toward evaluating the effectiveness of various fraud prediction algorithms. Accounting researches focus on testing multiple data mining and statistical models with the target of successfully detecting fraud. Research in data mining focuses explicitly on fraudulent financial statement detection. This is because the falsification in the financial statement domain is unique. The traits of this exclusivity are as follows:

1) There is a minor ratio between fraud – non-fraud companies (high-class imbalance)

2) Kinds of fraud may vary.

3) The ratio of false-positive to false-negative classification error cost is minor (cost imbalance)

4) The features which are utilised to spot fraud are rather noisy because attribute values of the same kind may indicate fraudulent and non-fraudulent actions.

5) Those who commit fraud try hard to hide the fraud by presenting the fraud companies' attribute values as the ones of non-fraud companies.

These exceptional qualities of the fraudster prevent their detection without experimental evaluation.

Financial statement fraud studies usually apply logistic regression as the primary method against which data mining models are put through examination. Many data mining algorithms that have worked as reliable predictors in different aspects have not been examined from financial statement fraud study. As a result, we do not have enough information about which algorithms are essential to discover what exact conditions one algorithm may be more suitable than another, distinguishing financial statement fraud and those predictors that are effective for different algorithms.

Extensive data mining algorithms were used in the forecast of financial report fraud. This study examined the most used algorithm and the most valuable forecasters for the algorithm when identifying FFS.

The answers obtained from these questions are significant to institutions, such as the HCMC, ASE, etc., and auditors. The result offers direction concerning which predictors and algorithms need to be utilised when developing novel simulations to discover financial report fraud. Auditors could employ these procedures and forecasters for improving customer selection, analytical techniques and audit planning. In contrast, the ASE and HCMC can leverage their findings for targeting audit engagements in which there is the likelihood of a case of financial report fraud by the firm.

Empirical results show that machine learning techniques are a competitive tool for financial report fraus risk evaluation. We see from the results given in Table 12 that computational intelligence methods have better success rates than statistical methods. Empirical findings show that the risk of financial report fraud can be evaluated by d of the proposed method classification. Specificity is slightly better for k-nn and NB than for LR and RF. DT and SVM have the lowest specificity. Also, the error rate shows how often the methods yield wrong results. Table 20 shows that the lowest error rate is demonstrated for k-nn followed by RF, DT, SVM, LR NB and Lasso. Precision shows how often a classifier is correct when it predicts fraud. The best results are for k-nn and RF. The proposed approach can help economic analysts, banks, investors, governments, and auditors decrease the risks associated with money. Additionally, the features and guidelines related to severe financial issues are understandable, hence crucial for audit in making the decision.

8.3.4 Are financial statements in Greece reliable? Have there been any accounting quality changes in Greece after the implementation of the IFRS?

According to agency theory, shareholders' conflicting interests (principals) and managers (agents) account for the use of creative accounting practices inside firms. Although this problem is taking place in the 1920s, it established in the 1980s and more in the 1990s. Firms falsify earnings at a high level, while other firms do not manage their earnings in some cases. According to the present study, it is observed that companies implementing IFRS show a smaller number of earnings levelling, reduced amount of managing earnings and increased prompt loss recognition.

Four metrics of earnings management used: three earnings levelling and one earning management means were used in this study. The first measure for levelling earnings centred on the unpredictability of net income ascertained by the total assets (Barth et al., 2005; Lang et al., 2006; Leuz et al., 2003). This study reports a higher variance of net income change as evidence of the lower level of earnings smoothing. Various factors which cannot be recognised in the financial reporting system causes the observed sensitivity of the net income changes. The second means of levelling earnings is by the proportion of net income's unpredictability (ΔNI) to the unpredictability of the operational flow of cash (ΔC). Organisations with greater unstable cash flow usually possess higher inconsistent net income; an observation of the second parameter in this study acts as a control. The third earnings levelling means in this study between accruals and cash flow. Finally, this research tries to estimate if firms manage earnings to small positive earnings (Barth et al., 2005; Burgstahler & Dichev, 1997; Leuz et al., 2003).

This study also measured the prompt loss recognition strategy for large negative net income(LNEG) (Lang et al., 2003; Lang et al., 2006).

The present study also used a dataset consisting of 231 Greek companies listed on the ASE from the years 2002 and 2015 and compared the quality in accounting before and post-implementation of the IFRS. This research observes more outstanding accounting in IFRS implementing firms. Limitations observed in this study is that one or more motivations may have been excluded in the model evaluating earnings management as a degree of the earnings quality.

Results from this study showed higher quality in accounting for companies that apply IFRS. Accounting standards, their explanation, implementation and litigation are the accounting amounts compared with features associated with financial reporting system communication. This study also observed that the companies that apply the IFRS demonstrated less earning levelling, reduced earnings management, and increased prompt loss recognition. This research contributes to knowledge by adding to the growing literature on the implementation of creative accounting and the IFRS accounting quality in Greece's diverse cultural and regulatory systems.

8.4 Future Research Suggestions

The implementation of the IFRS led to much accounting research on an international level. The optional or obligatory performance of the IFRS has led to many studies of its impact on equity and debt markets (Barth et al., 2008; Christensen et al., 2009; Daske et al., 2008; Jeanjean & Stolowy, 2008; Nobes, 2006; Platikanova & Nobes, 2006). Also, research has focused on characteristics of accounting quality after implementing the IFRS in several countries or in multi-country settings that have not been referred to in this thesis. However, this study may give the occasion fo further study.

This study designed to study the implementation of IFRS in Greece. Future research may study whether firms comply with IFRS in Greece; in other words, study to what extent Greek companies utilise IFRS and in what detail. This means that future research may examine if companies implement and use IFRS properly. A further aspect of being discussed could be the study of specific standards for companies of small and medium-size or governmental ones and how these standards have been implemented and utilised in the Greek market.

Further studies can investigate the application of the new law in accounting in Greek firms. This new law shares many similarities with the IFRS. Thus, future research can compare how the new law supports the IFRS and whether the firms have adapted to the new law.

Finally, future research can investigate the factors that influence Greece combined with corporate governance attributes.

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Appendix

Table 29: Endogeneity Test for profitability ratios

ivregress 2sls y1 x20 (x28 = x20 x13 x33 x29 x18 x19 x25 x34)

Instrumental variables (2SLS) regression

Number of obs = 2469
Wald chi2(2) = 27.91
Prob > chi2=0.0000
R-squared =0.0020
Root MSE = .49425

Y_1	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
X28	-.0155853	.004492	-3.47	0.001	-.0243895	-.0067811
X20	.0040511	.0028179	1.44	0.151	-.0014719	.0095742
_cons	.4230045	.0099975	42.31	0.000	.4034097	.4425993

Instrumented: x28

Instrumentsx20 x13 x33 x29 x18 x19 x25 x34

Perform test of endogeneity

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = 9.00986 (p = 0.0027))

Wu-Hausman F(1,2465) =9.02821 (p = 0.0027)

Report first stage regression

First-stage regression summary statistics

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(7,2460)	Prob > F
X28	0.7759	0.7752	0.3866	221.531	0.0000

Minimum eigenvalue statistic = 221.531

\# of endogenous regressors: 1

Ho: Instruments are weak

\# of excluded instruments: 7

	5%	10%	20%	30%
2SLS relative bias	19.86	11.29	6.73	5.07
	10%	15%	20%	25%
2SLS Size of nominal 5% Wald test	31.50	17.38	12.48	9.93
LIML Size of nominal 5% Wald test	4.18	3.18	2.73	2.49

Perform tests of overdentifying restriction

Tests of overidentifying restrictions:

Sargan (score) chi2(6) = 106.804 (p = 0.0000)

Basmann chi2(6) =111.226 (p = 0.0000)

Table 30: Endogeneity Test for liquidity ratios

ivregress 2sls y1 x24 (x26 = x27 x21 x22 x34)

Instrumental variables (2SLS) regression Number of obs = 2469
Wald chi2(2) = 32.47
Prob > chi2=0.0000
R-squared =
Root MSE = .51538

Y_1	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
X26	-2.994767	.8202714	-3.65	0.000	-4.602469	-1.387065
X24	-.0003361	.0061347	-0.05	0.956	-.0123598	.0116876
_cons	.5761749	.0341261	16.88	0.000	.5092889	.6430609

Instrumented: x26

Instrumentsx24 x27 x21 x22 x34

Perform test of endogeneity

Tests of endogeneity
Ho: variables are exogenous

Durbin (score) chi2(1) = 8.25762 (p = 0.0041)
Wu-Hausman F(1,2465) =8.2719 (p = 0.0041)

Report first stage regression

First-stage regression summary statistics

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(3,2463)	Prob > F
X26	0.0676	0.0657	0.0296	20.7379	0.0000

Minimum eigenvalue statistic = 18.7547

\# of endogenous regressors: 1
Ho: Instruments are weak # of excluded instruments: 4

	5%	10%	20%	30%
2SLS relative bias	16.85	10.27	6.71	5.34
	10%	15%	20%	25%
2SLS Size of nominal 5% Wald test	24.58	13.96	10.26	8.31
LIML Size of nominal 5% Wald test	5.44	3.87	3.30	2.98

Perform tests of overdentifying restriction

Tests of overidentifying restrictions:

Sargan (score) chi2(3) =88.2966 (p = 0.0000)
Basmann chi2(3) =91.3488 (p = 0.0000)

Table 31: Endogeneity Test for solvency ratios

ivregress 2sls y1 x1 (x7 = x1 x5 x2 x6 x4 x31 x34)

Instrumental variables (2SLS) regression

Number of obs = 2469
Wald chi2(2) = 59.29
Prob > chi2=0.0000
R-squared =0.0409
Root MSE = .48453

Y_1	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
X7	.1205743	.0156587	7.70	0.000	.0898838	.1512649
X1	1.43e-10	2.71e-11	5.27	0.000	8.96e-11	1.96e-10
_cons	.3555233	.0125312	28.37	0.000	.3309626	.380084

Instrumented: x7

Instruments x1 x5 x2 x6 x4 x31 x34

Perform test of endogeneity

Tests of endogeneity
Ho: variables are exogenous

Durbin (score) chi2(1) =5.03105 (p = 0.0249)
Wu-Hausman F(1,2465) =5.03315 (p = 0.0250)

Report first stage regression

First-stage regression summary statistics

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(6,2461)	Prob > F
X7	0.4548	0.4532	0.4544	341.632	0.0000

Minimum eigenvalue statistic = 341.632

Ho: Instruments are weak

# of endogenous regressors: 1
# of excluded instruments: 6

	5%	10%	20%	30%
2SLS relative bias	19.28	11.12	6.76	5.15
	10%	15%	20%	25%
2SLS Size of nominal 5% Wald test	29.18	16.23	11.72	9.38
LIML Size of nominal 5% Wald test	4.45	3.34	2.87	2.61

Perform tests of overdentifying restriction

Tests of overidentifying restrictions:

Sargan (score) chi2(5) =101.414 (p = 0.0000)
Basmann chi2(5) =105.416 (p = 0.0000)

Table 32: Endogeneity Test for activity ratios

ivregress 2sls y1 x32 (x9 = x23 x8 x14 x12 x11 x34)

Instrumental variables (2SLS) regression   Number of obs = 2469
Wald chi2(2) = 2.61
Prob > chi2=0.2705
R-squared =
Root MSE = .78582

Y_1	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
X9	.0594503	.0367639	1.62	0.106	-.0126055	.1315062
X32	7.26e-10	1.99e-10	3.65	0.000	3.37e-10	1.12e-09
_cons	.3777596	.0278271	13.58	0.000	.3232195	.4322998

Instrumented: x9

Instruments x32 x23 x8 x14 x12 x11 x34

Perform test of endogeneity

Tests of endogeneity
Ho: variables are exogenous

Durbin (score) chi2(1) =6.3732 (p = 0.0116)
Wu-Hausman F(1,2465) = 6.37934 (p = 0.0116)

Report first stage regression

First-stage regression summary statistics

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(6,2461)	Prob > F
X9	0.0017	-0.0012	0.0017	.679015	0.6667

Minimum eigenvalue statistic = .1547.4

\# of endogenous regressors: 1
Ho: Instruments are weak   # of excluded instruments: 6

	5%	10%	20%	30%
2SLS relative bias	19.28	11.12	6.76	5.15
	10%	15%	20%	25%
2SLS Size of nominal 5% Wald test	29.18	16.23	11.72	9.38
LIML Size of nominal 5% Wald test	4.45	3.34	2.87	2.61

Perform tests of overdentifying restriction

Tests of overidentifying restrictions:

Sargan (score) chi2(5) =19.4253 (p = 0.0016)
Basmann chi2(5) =19.5159 (p = 0.0015)

Table 33: Endogeneity Test for structure ratios

ivregress 2sls y1 x10 (x15 = x16 x30 x17 x3 x34)

Instrumental variables (2SLS) regression	Number of obs = 2469
	Wald chi2(2) = 0.84
	Prob > chi2=0.6564
	R-squared =0.0144
	Root MSE = .49117

Y_1	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
X15	1.03e-10	2.59e-11	3.98	0.000	5.24e-11	1.54e-10
X10	-.0597989	.0651661	-0.92	0.359	-.1875221	.0679244
_cons	.4177256	.0134376	31.09	0.000	.3913885	.4440628

Instrumented: x15

Instrumentsx10 x16 x30 x17 x3 x34

Perform test of endogeneity

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) =7.42792 (p = 0.0064)

Wu-Hausman F(1,2465) =7.43827 (p = 0.0064)

Report first stage regression

First-stage regression summary statistics

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(5,2462)	Prob > F
X15	0.7587	0.7581	0.7586	1547.4	0.0000

Minimum eigenvalue statistic = .1547.4

	# of endogenous regressors: 1
Ho: Instruments are weak	# of excluded instruments: 5

	5%	10%	20%	30%
2SLS relative bias	18.37	10.83	6.77	5.25
	10%	15%	20%	25%
2SLS Size of nominal 5% Wald test	26.87	15.09	10.98	8.84
LIML Size of nominal 5% Wald test	4.84	3.56	3.05	2.77

Perform tests of overdentifying restriction

Tests of overidentifying restrictions:

Sargan (score) chi2(4) =49.3992 (p = 0.0000)

Basmann chi2(4) =50.2648 (p = 0.0000)

Table 34: Endogeneity Test for investment ratios

ivregress 2sls y1 x35 (x36 = x35 x34)

Instrumental variables (2SLS) regression				Number of obs = 2469		
				Wald chi2(2) = 0.04		
				Prob > chi2=0.9809		
				R-squared =		
				Root MSE = 14.136		
Y_1	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
X36	-1.369327	7.116844	-0.19	0.847	-15.31808	12.57943
X35	-.0000768	.0003952	-0.19	0.846	-.0008513	.0006977
_cons	3.094483	13.8637	0.22	0.823	-24.07788	30.26684

Instrumented: x36

Instrumentsx35 x34

Perform test of endogeneity

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) =30.3228 (p = 0.0000)

Wu-Hausman F(1,2465) =30.6501 (p = 0.0000)

Report first stage regression

First-stage regression summary statistics

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(1,2466)	Prob > F
X36	0.0039	0.0031	0.0000	.037095	0.8473

Minimum eigenvalue statistic = .037095

	# of endogenous regressors: 1
Ho: Instruments are weak	# of excluded instruments: 5

	5%	10%	20%	30%
2SLS relative bias	(not available)			
	10%	15%	20%	25%
2SLS Size of nominal 5% Wald test	16.38	8.96	6.66	5.53
LIML Size of nominal 5% Wald test	16.38	8.96	6.66	5.53

Table 35:The selected vector according to CVSR in K-nn

k-nn		
	vector	CVSR (%)
1	[x3]	60.35
2	[x3] [x34]	68.29
3	[x3] [x12][x34]	79.63
4	[x1][x3] [x12][x34]	84.61
5	[x1][x3] [x12][x25][x34]	86.11
6	[x1][x3][x11] [x12][x25][x34]	87.69
7	[x1][x3][x11] [x12][x14][x25][x34]	88.05
8	[x1][x3][x11] [x12][x14][x21][x25][x34]	88.42
9	[x1][x3][x11] [x12][x14][x21][x25][x32][x34]	88.90
10	[x1][x3][x4][x11] [x12][x14][x21][x25][x32][x34]	89.11

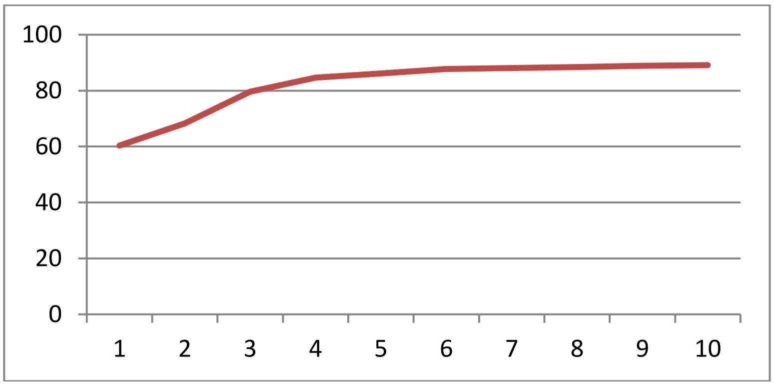


Figure 4: K-nn vector

Table 36: The selected vector according to CVSR in NB

NB		
1	[x7]	63.87
2	[x7][X15]	65.25
3	[x7][X15][X29]	65.70
4	[X5][x7][X15][X29]	66.51
5	[X5][x7][X15][X24][X29]	66.63
6	[X5][X6][x7][X15][X24][X29]	66.87
7	[X5][X6][x7][X15][X24][X29]	67.52
8	[X5][X6][x7][X15][X24][X26][X29]	67.72
9	[X5][X6][x7][X15][X24][X26][X29][X34]	68.00
10	[X5][X6][x7][X15][X17][X24][X26][X29][X34]	68.00
11	[X5][X6][x7][X15][X17][X24][X26][X29][X30][X34]	68.09
12	[X2][X5][X6][x7][X15][X17][X24][X26][X29][X30][X34]	68.29

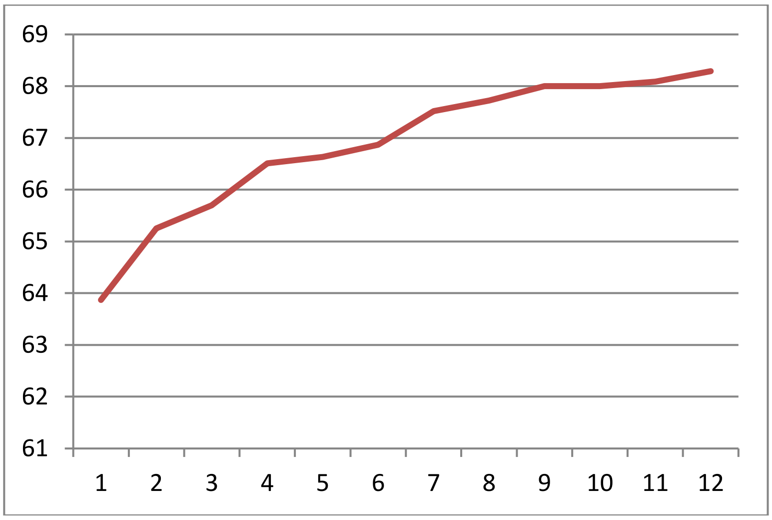


Figure 5: NB vector

Table 37: The selected vector according to CVSR in LR

LR		
1	[X29]	61.97
2	[X2][X29]	65.82
3	[X2][X16][X29]	67.27
4	[X2][X16][X17][X29]	68.25
5	[X2][X16][X17][X26][X29]	68.89
6	[X2][X3][X16][X17][X26][X29]	69.22
7	[X2][X3][X16][X17][X19][X26][X29]	69.50

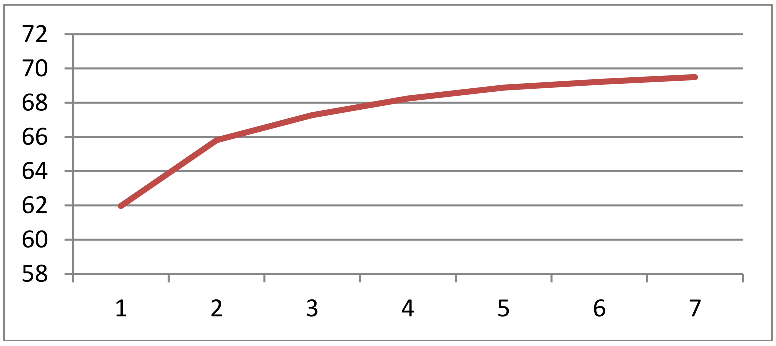


Figure 6: LR vector

Table 38: The selected vector according to CVSR in SVM

SVM		
1	[X7]	63.63
2	[X2][X7]	66.10
3	[X2][X7][X16]	67.72
4	[X2][X7][X16][X34]	69.54
5	[X2][X7][X16][X23][X34]	72.34
6	[X2][X7][X16][X23][X26]	73.63
7	[X2][X7][X16][X23][X26][X34]	74.85
8	[X2][X7][X16][X17][X23][X26][X34]	76.06
9	[X2][X3][X7][X16][X17][X23][X26][X34]	76.51
10	[X2][X3][X7][X16][X17][X18][X23][X26][X34]	77.16
11	[X2][X3][X7][X16][X17][X18][X23][X26][X34]	77.52
12	[X2][X3][X7][X10][X16][X17][X18][X23][X26][X34]	77.81
13	[X2][X3][X4][X7][X10][X16][X17][X18][X23][X26][X34]	77.97
14	[X2][X3][X4][X5][X7][X10][X16][X17][X18][X23][X26][X34]	78.05
15	[X2][X3][X4][X5][X7][X10][X16][X17][X18][X23][X26][X34][X35]	78.13

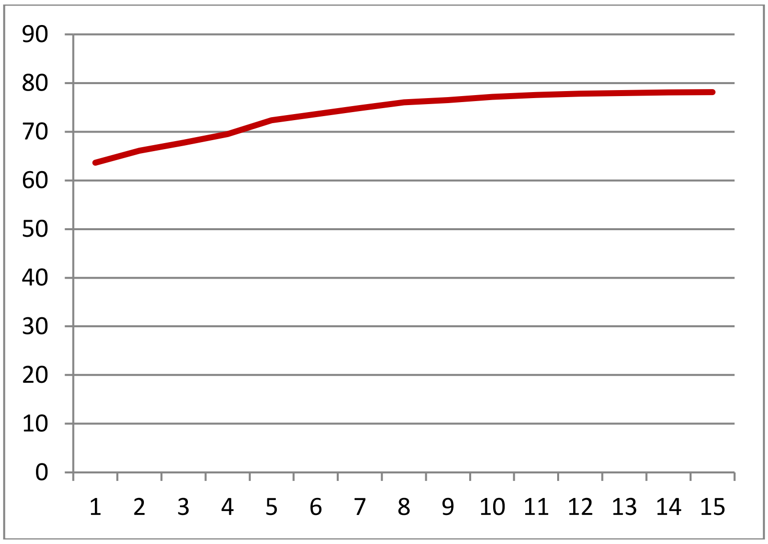


Figure 7:SVM vector

Table 39: The selected vector according to CVSR in DT

DT		
1	[X4]	62.78
2	[X4][X15]	66.46
3	[X4][X15][X34]	74.36
4	[X4][X15][X17][X34]	78.62
5	[X4][X10][X15][X17][X34]	80.24
6	[X4][X9][X10][X15][X17][X34]	80.80

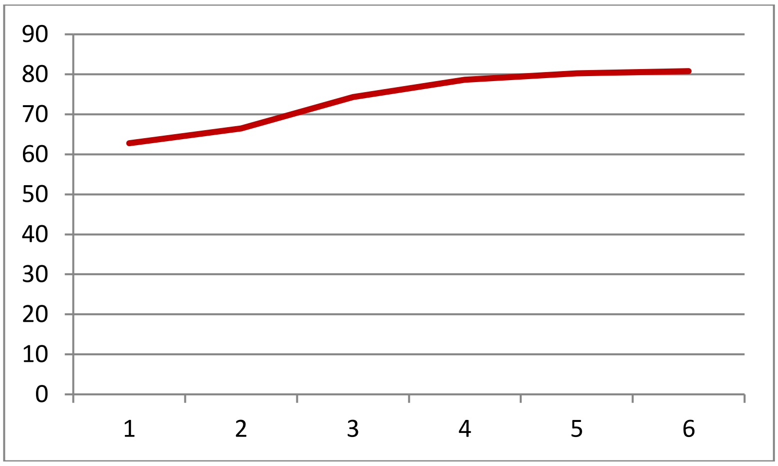


Figure 8: DT vector

Table 40: The selected vector according to CVSR in RF

RF		
1	[X4]	60.75
2	[X4][X16]	69.91
3	[X4][X16][X34]	78.49
4	[X4][X16][X17][X34]	82.54
5	[X4][X16][X17][X23][X34]	84.29
6	[X4][X14][X16][X17][X23][X34]	84.73
7	[X4][X11][X14][X16][X17][X23][X34]	85.30

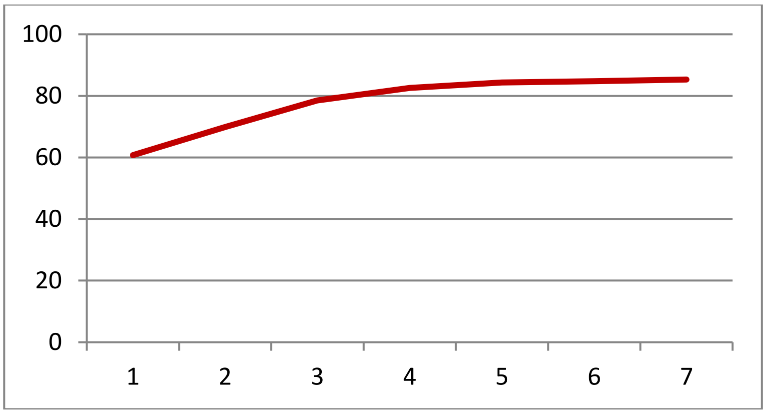


Figure 9: RF vector

Lasso results

- when α=0,001 the results of the model are:

W=[w1,w2,…,w36] = [0.0, 0.06994023246062524, 0.0, -0.0, 0.0, -0.0, 0.024441230912531916, 0.0, 0.0, -0.0, 0.0, 0.0, -0.0, 0.0, 0.0, 0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0023108235357471294, -0.0, -0.0, 0.0, -0.043705433151101244, -0.0, -0.0, -0.26681697753654693, 0.0, -0.0, 0.0, -0.0, -0.0010903074415581414, -0.0, 0.0]

So if we choose the non zero coefficients the most important variables are:['x2', 'x7', 'x22', 'x26', 'x29', 'x34']

- when α=0,1 the results of the model are:

W=[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, -0.0, 0.0, 0.0, -0.0, 0.0, 0.0, 0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, 0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, 0.0, -0.0, -0.0, -0.0, 0.0]

All the coefficients are zero in absolute values.

- when α=0,01 the results of the model are:

w=[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, -0.0, 0.0, 0.0, -0.0, 0.0, 0.0, 0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, 0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, 0.0, -0.0, -0.0, -0.0, 0.0]

All the coefficients are zero in absote vaues again.

- when α=0,0001 the results of the model are:

W=[-1.3822509993918832e-11, 0.25724755187600185, -0.0, -0.00037061633041658476, -0.0, -0.005381234761558491, 0.04413441249427377, 0.004664580931036816, 0.0008762599743373508, -0.05141746885385789, 0.001478774782164955, 0.0, -0.0, 0.0, -0.0, -0.15132474586673653, -0.06800512890370251, -0.0, -0.03245229813840161, -0.0005332231772459781, -2.438165781834634e-10, 0.0, -0.04908175890709633, -0.0, 0.000222052016983391, -0.5384706589925031, 0.004655933069427372, -0.0, -0.3290547793137794, 0.00502072784584208, 0.0, 5.326027728961141e-10, 8.030775342646714e-11, -0.013885352615616579, -6.935883378570868e-07, 0.0021566043158792675]

The Selected variables=['x2', 'x6', 'x7', 'x8', 'x10', 'x11', 'x16', 'x17', 'x19', 'x23', 'x26', 'x27', 'x29', 'x30', 'x34', 'x36']

- when α=0,0005 the results of the model are:

w= [0.0, 0.09686553002157669, 0.0, -0.0, 0.0, -0.0, 0.04568625359548907, -0.0, 0.0, -0.0, 0.0, 0.0, -0.0, 0.0, 0.0, 0.0, -0.0, -0.025473096180750797, -0.0, -0.0, -1.2709406474470737e-11, -0.0, -0.00764499452709898, -0.0, 0.0, -0.3026183129984837, -0.0, -0.0, -0.3366753459539497, 0.0, 0.0, 1.9537999925027322e-10, -0.0, -0.008131559843167208, -0.0, 0.0]

The selected variables are['x2', 'x7', 'x18', 'x23', 'x26', 'x29', 'x34']

So different values for α the model calculates different weights. So we use the cross validation for the best result.

so

- when $\alpha > 0.001$ we can not choose any input as the value is large.
- when $\alpha = 0$the second part of the function does not exist and the method of OLS is for all inputs.

So we have to determine the best value for α where $\alpha \in [0, 0.001]$

So we choose the value with the best CVSR.

The best value is $\alpha = 1.46 \cdot 10^{-4}$and the result is :

W = [-0.0, 0.14108480963677328, -0.0, -0.0001967068548312636, -0.0, -0.0007026980090445352, 0.056728350557336764, 0.00028298779702108976, 0.0006898791534142946, -0.01237401766921746, 0.0011342532802037966, 0.0, -0.0, 0.0, 0.0, -0.021588015967836372, -0.04139233326277225, -0.0, -0.03673890004485728, -0.00033232521078028517, -2.1365110172437436e-10, -0.0, -0.032960030105095, 0.0, 0.00019026889857566356, -0.4892997344992109, 0.0, -0.0, -0.35317151539196917, 0.0020035988926494206, 0.0, 4.496748265094018e-10, 2.1222079501407597e-11, -0.013274028899160632, -4.884408326691186e-07, 0.001944758087706189]

The selected variables are:

['x2', 'x4', 'x6', 'x7', 'x8', 'x9', 'x10', 'x11', 'x16', 'x17', 'x19', 'x20', 'x23', 'x25', 'x26', 'x29', 'x30', 'x34', 'x36']

Tests of Heteroscedasticity, Multicollinearity and Endogeneity

$$\Delta NI_{it} = \alpha_0 + \alpha_1 SIZE_{it} + \alpha_2 GROWTH_{it} + \alpha_3 LEV_{it} + \alpha_4 DISSUE_{it} + \alpha_5 TURN_{it} + \alpha_6 CF_{it} + \alpha_7 AUD_{it} + \varepsilon_{it} \quad \textbf{(21)}$$

Table 41: Heteroscedasticity Test for ΔNI_{it}

Source	SS	df	MS
Model	8.810266	8	1.101283
Residual	1501.808	1787	0.840408
Total	1510.619	1795	0.84157

Number of obs = 1796
F(8, 1787) = 1.31
Prob > F = 0.2336
R-squared = 0.0058
Adj R-squared = 0.0014
Root MSE = .91674

DNI	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
SIZE	-0.09985	.0332399	-3.00	0.003	-.1650405	-.0346543
GROWTH	-0.00041	.0080292	-0.05	0.960	-.0161535	.0153417
LEV	-0.00027	.0013038	-0.21	0.834	-.0028298	.0022846
DISSUE	-5.2E-05	.0007534	-0.07	0.945	-.0015293	.001426
TURN	-0.02237	.0271486	-0.82	0.410	-.0756122	.0308803
CF	2.61E-10	4.30e-10	0.61	0.543	-5.82e-10	1.10e-09
AUD	0.033634	.0506069	0.66	0.506	-.065621	.1328888
SECTOR	-0.00022	.0060891	-0.04	0.971	-.012162	.0117231
_cons	0.769068	.2406494	3.20	0.001	.2970841	1.241052

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: SIZE GROWTH LEV DISSUE TURN CF AUD SECTOR

chi2(8) = 1668.55
Prob > chi2 = 0.0000

Table 42 Multicollinearity Testfor ΔNI_{it}

Variable	VIF	1/VIF
GROWTH	1.99	0.50178
DISSUE	1.94	0.515324
SIZE	1.19	0.843833
AUD	1.11	0.899664
CF	1.1	0.907373
TURN	1.04	0.95896
SECTOR	1.03	0.974599
LEV	1	0.996032
Mean VIF	1.3	

Table 43: Endogeneity Test for ΔNI_{it}

Instrumental variables (2SLS) regression

Number of obs = 1796
Wald chi2(2) = 8.66
Prob > chi2 = 0.0131
R-squared = .
Root MSE = .94013

DNI	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
CF	-4.06E-09	1.38E-09	-2.94	0.003	-6.76E-09	-1.35E-09
LEV	-0.00022	0.001334	-0.16	0.869	-0.00284	0.002396
_cons	0.075088	0.026431	2.84	0.004	0.023285	0.126891

Instrumented: CF
Instruments: LEV SIZE GROWTH DISSUE TURN AUD SECTOR

Perform test of endogeneity

Tests of endogeneity
Ho: variables are exogenous

Durbin (score) chi2(1) = 9.33226 (p = 0.0023)
Wu-Hausman F(1,1792) = 9.36011 (p = 0.0023)

Report first stage regression

First-stage regression summary statistics

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(6,1788)	Prob > F
CF	0.0926	0.0891	0.0926	30.4204	0.000000

Minimum eigenvalue statistic = 30.4204
Critical Values # of endogenous regressors: 1
Ho: Instruments are weak # of excluded instruments: 6

	5%	10%	20%	30%
2SLS relative bias	19.28	11.12	6.76	5.15
	10%	15%	20%	25%
2SLS Size of nominal 5% Wald test	29.18	16.23	11.72	9.38
LIML Size of nominal 5% Wald test	4.45	3.34	2.87	2.61

Perform tests of overdentifying restriction

Tests of overidentifying restrictions:
Sargan (score) chi2(5) = .953129 (p = 0.9663)
Basmann chi2(5) = .949387 (p = 0.9665)

$$\Delta CF_{it} = \alpha_0 + \alpha_1 SIZE_{it} + \alpha_2 GROWTH_{it} + \alpha_3 LEV_{it} + \alpha_4 DISSUE_{it} + \alpha_5 TURN_{it} + \alpha_6 CF_{it} + \alpha_7 AUD_{it} + \varepsilon_{it} \quad (22)$$

Table 44: Heteroscedasticity Test for ΔCF_{it}

Source	SS	df	MS
Model	3658.62456	7	522.660651
Residual	579145.382	1638	353.56861
Total	582804.007	579145.3	354.28815

Number of obs = 1646
F(7, 1638) = 1.48
Prob > F = 0.1706
R-squared = 0.0063
Adj R-squared = 0.002
Root MSE = 18.803

#DCF	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
SIZE	1.943674	.7199029	2.70	0.007	.5316467	3.355701
GROWTH	-.0854366	.1656593	-0.52	0.606	-.410363	0.2394898
LEV	-.0317394	.026892	-1.18	0.238	-.0844857	0.0210069
DISSUE	-.0161879	.0155039	-1.04	0.297	-.0465975	0.0142217
TURN	-.0539402	.5665007	-0.10	0.924	-1.165082	1.057202
CF	-6.24e-09	8.85e-09	-0.70	0.481	-2.36e-08	1.11E-08
AUD	-.7126718	1.061842	-0.67	0.502	-2.795383	1.370039
_cons	-14.27183	5.230905	-2.73	0.006	-24.5318	-4.011867

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: SIZE GROWTH LEV DISSUE TURN CF AUD

chi2(7) = 325.83
Prob > chi2 = 0.0000

Table 45: Multicollinearity Test for ΔCF_{it}

Variable	VIF	1/VIF
GROWTH	1.99	0.502167
DISSUE	1.95	0.51249
SIZE	1.18	0.848814
CF	1.11	0.904604
AUD	1.09	0.919992
TURN	1.03	0.968678
LEV	1	0.995527
Mean VIF	1.34	

Table 46: Endogeneity Test for ΔCF_{it}

Instrumental variables (2SLS) regression

Number of obs=1646
Wald chi2(2) = 6.49
Prob >chi2 =0.0390
R-squared = .
Root MSE = 19.1

DCF	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
CF	6.06E-08	2.77E-08	2.19	0.028	6.38E-09	1.15E-07
LEV	-0.03505	0.027255	-1.29	0.198	-0.08847	0.01837
_cons	-0.90298	0.5645557	-1.6	0.11	-2.00949	0.203527

Instrumented: CF
Instruments: LEV SIZE GROWTH DISSUE TURN AUD

Perform test of endogeneity

Tests of endogeneity
Ho: variables are exogenous

Durbin (score) chi2(1) = 5.44488 (p = 0.0196)
Wu-Hausman F(1,1642) = 5.44968 (p = 0.0197)

Report first stage regression

First-stage regression summary statistics

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(5,1639)	Prob > F
CF	0.0954	0.0921	0.0954	34.5668	0.000000

Minimum eigenvalue statistic = 34.5668

Critical Values # of endogenous regressors: 1
Ho: Instruments are weak # of excluded instruments: 5

	5%	10%	20%	30%
2SLS relative bias	18.37	10.83	6.77	5.25
	10%	15%	20%	25%
2SLS Size of nominal 5% Wald test	26.87	15.09	10.98	8.84

Perform tests of overdentifying restriction

Tests of overidentifying restrictions:
Sargan (score) chi2(4) = 3.05818 (p = 0.5481)
Basmann chi2(4) = 3.05084 (p = 0.5494)

$$CF_{it} = \alpha_0 + \alpha_1 SIZE_{it} + \alpha_2 GROWTH_{it} + \alpha_3 LEV_{it} + \alpha_4 DISSUE_{it} + \alpha_5 TURN_{it} + \alpha_6 AUD_{it} + \varepsilon_{it} \quad (23)$$

Table 47: Heteroscedasticity Test for CF_{it}

Source	SS	df	MS
Model	4.7392e+17	6	7.8986e+16
Residual	4.5616e+18	1794	2.5427e+15
Total	5.0355e+18	1800	2.7975e+15

Number of obs = 1801
F(6, 1794) = 31.06
Prob > F = 0
R-squared = 0.0941
Adj R-squared = 0.0911
Root MSE = 50000000

CF	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
SIZE	2.08e+07	1754815	11.87	0.000	1.74e+07	2.43E+07
GROWTH	552702.3	441081.5	1.25	0.210	-312385.2	1417790
LEV	647.7283	71711.09	0.01	0.993	-139998.3	141293.8
DISSUE	61334.74	41402.14	1.48	0.139	-19866.75	142536.2
TURN	4203536	1486367	2.83	0.005	1288343	7118729
AUD	3027566	2752395	1.10	0.271	-2370671	8425803
_cons	-1.46e+08	1.27e+07	11.51	0.000	-1.71e+08	-1.21E+08

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: SIZE GROWTH LEV DISSUE TURN AUD

chi2(6) = 5648.64
Prob > chi2 = 0.0000

Table 48: Multicollinearity Test for CF_{it}

Variable	VIF	1/VIF
GROWTH	1.99	0.502806
DISSUE	1.94	0.516268
SIZE	1.1	0.910406
AUD	1.09	0.917009
TURN	1.03	0.96693
LEV	1	0.996105
Mean VIF	1.36	

$$ACC_{it} = \alpha_0 + \alpha_1 SIZE_{it} + \alpha_2 GROWTH_{it} + \alpha_3 LEV_{it} + \alpha_4 DISSUE_{it} + \alpha_5 TURN_{it} + \alpha_6 AUD_{it} + \varepsilon_{it} \quad (24)$$

Table 49: Heteroscedasticity Test for ACC_{it}

Source	SS	df	MS
Model	2.03E+16	6	3.3832e+15
Residual	1.11E+19	2274	4.9023e+15
Total	1.12E+19	2280	4.8983e+15

Number of obs = 2281
F(6, 2274) = 0.69
Prob > F =0.6577
R-squared = 0.0018
Adj R-squared =-0.0008
Root MSE = 70000000

ACC	Coef.	Std. Err.	t	P>t	[95%Conf.	Interval]
SIZE	-455771	2116007	-0.22	0.829	-4605278	3693737
GROWTH	-125719	283011.2	-0.44	0.657	680706.3	429267.8
LEV	-31792.7	86758.57	-0.37	0.714	-201927	138341.5
DISSUE	52539.38	45511.31	1.15	0.248	-36708.66	141787.4
TURN	210595.3	1819528	0.12	0.908	-3357514	3778704
AUD	-3340518	3399831	-0.98	0.32	-1.00e+07	3326576
_cons	-4159110	1.53e+07	-0.27	0.786	-3.42e+07	2.59E+07

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: SIZE GROWTH LEV DISSUE TURN AUD

chi2(6) = 2182.98
Prob > chi2 = 0.0000

Table 50: Multicollinearity Test for ACC_{it}

Variable	VIF	1/VIF
GROWTH	1.23	0.815082
DISSUE	1.22	0.818563
SIZE	1.09	0.917072
AUD	1.08	0.922005
TURN	1.03	0.97243
LEV	1	0.999287
Mean VIF	1.11	

$$IAS(0,1)_{it} = \alpha_0 + \alpha_1 SPOS_{it} + \alpha_2 SIZE_{it} + \alpha_3 GROWTH_{it} + \alpha_4 LEV_{it} + \alpha_5 DISSUE_{it} + \alpha_6 TURN_{it} + \alpha_7 CF_{it} + \alpha_8 AUD_{it} + \varepsilon_{it} \qquad (25)$$

Table 51: Heteroscedasticity Test for $SPOS_{it}$

Source	SS	df	MS
Model	18.8633164	8	2.35791455
Residual	286.683602	1792	.159979689
Total	305.546918	1800	.169748288

Number of obs = 1801
F(8, 1792) = 14.74
Prob > F =0
R-squared = 0.0617
Adj R-squared = 0.0575
Root MSE = 0.39997

IAS	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
SPOS	-.0583894	.0239965	-2.43	0.01	-.1054534	-0.0113253
SIZE	-.1358607	.0144784	-9.38	0.000	-.164257	-0.1074644
GROWTH	.0096214	.0035006	2.75	0.006	.0027558	0.016487
LEV	.0000815	.0005688	0.14	0.886	-.0010341	0.0011971
DISSUE	-.0000121	.0003287	-0.04	0.971	-.0006567	0.0006325
TURN	-.0065523	.0118169	-0.55	0.579	-.0297288	0.0166241
CF	6.70e-10	1.87e-10	3.58	0.000	3.03e-10	1.04E-09
AUD	.0992395	.0219138	4.53	0.000	.0562603	0.1422188
_cons	1.752848	.1042913	16.81	0.000	1.548303	1.957394

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: SPOS SIZE GROWTH LEV DISSUE TURN CF AUD

chi2(8) = 115.63
Prob > chi2 = 0.0000

Table 52: Multicollinearity Test for $SPOS_{it}$

Variable	VIF	1/VIF
GROWTH	1.99	0.502252
DISSUE	1.94	0.515429
SIZE	1.19	0.841524
CF	1.11	0.903926
AUD	1.1	0.910193
TURN	1.04	0.962519
SPOS	1.01	0.989551
LEV	1	0.996095
Mean VIF	1.3	

Table 53: Endogeneity Test for $SPOS_{it}$

Instrumental variables (2SLS) regression — Number of obs = 1845
Wald chi2(2) = 6.89
Prob > chi2 = 0.0318
R-squared = .
Root MSE = 1.091

IAS	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
SPOS	-2.64674	1.009536	-2.62	0.009	-4.6254	-0.66809
LEV	-1.6E-05	0.001549	-0.01	0.992	-0.00305	0.003021
_cons	1.29737	0.196093	6.62	0	0.913036	1.681705

Instrumented: SPOS
Instruments: LEV SIZE GROWTH DISSUE TURN CF

Perform test of endogeneity

Tests of endogeneity
Ho: variables are exogenous

Durbin (score) chi2(1) = 46.556 (p = 0.0000)
Wu-Hausman F(1,1841) = 47.6576 (p = 0.0000)

Report first stage regression

First-stage regression summary statistics

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(4,1838)	Prob > F
CF	0.0041	0.0008	0.0041	1.22571	0.297800

Minimum eigenvalue statistic = 1.50357

Critical Values — # of endogenous regressors: 1
Ho: Instruments are weak — # of excluded instruments: 5

	5%	10%	20%	30%
2SLS relative bias	18.37	10.83	6.77	5.25
	10%	15%	20%	25%
2SLS Size of nominal 5% Wald test	26.87	15.09	10.98	8.84
LIML Size of nominal 5% Wald test	4.84	3.56	3.05	2.77

Perform tests of overdentifying restriction

Tests of overidentifying restrictions:

Sargan (score) chi2(4) = 5.05979 (p = 0.2812)
Basmann chi2(4) = 5.05446 (p = 0.2818)

$$IAS(0,1)_{it} = \alpha_0 + \alpha_1 LNEG_{it} + \alpha_2 SIZE_{it} + \alpha_3 GROWTH_{it} + \alpha_4 LEV_{it} + \alpha_5 DISSUE_{it} + \alpha_6 TURN_{it} + \alpha_7 CF_{it} + \alpha_8 AUD_{it} + \varepsilon_{it} \quad (26)$$

Table 54:Heteroscedasticity Test for$LNEG_{it}$

Source	SS	df	MS
Model	19.1377625	8	2.39222031
Residual	286.362238	1791	.15988958
Total	305.5	1799	.169816565

Number of obs = 1800
F(8, 1791) = 14.96
Prob > F =0
R-squared = 0.0626
Adj R-squared = 0.0585
Root MSE =0.39986

IAS	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
LNEG	.1037504	.0371886	2.79	0.005	.0308129	0.1766879
SIZE	-.1270929	.0149517	-8.50	0.000	-.1564175	-0.0977683
GROWTH	.0096335	.0034997	2.75	0.006	.0027696	0.0164975
LEV	.0000802	.0005687	0.14	0.888	-.0010351	0.0011955
DISSUE	-.0000241	.0003285	-0.07	0.942	-.0006684	0.0006203
TURN	-.0049593	.0118326	-0.42	0.675	-.0281664	0.0182478
CF	6.72e-10	1.87e-10	3.59	0.000	3.05e-10	1.04E-09
AUD	.0998559	.0218767	4.56	0.000	.0569493	0.1427624
_cons	1.66815	.108749	15.34	0.000	1.454861	1.881438

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: LNEG SIZE GROWTH LEV DISSUE TURN CF AUD

chi2(8) = 113.28
Prob > chi2 = 0.0000

Table 55:Multicollinearity Test for$LNEG_{it}$

Variable	VIF	1/VIF
GROWTH	1.99	0.502245
DISSUE	1.94	0.515624
SIZE	1.27	0.789275
CF	1.11	0.904539
AUD	1.1	0.912968
LNEG	1.08	0.925819
TURN	1.04	0.959755
LEV	1	0.99609
Mean VIF	1.32	

Table 56:Endogeneity Test for $LNEG_{it}$

Instrumental variables (2SLS) regression

Number of obs = 1844
Wald chi2(2) = 42.69
Prob > chi2 = 0.0000
R-squared = .
Root MSE = .4595

IAS	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
LNEG	0.968853	0.148483	6.53	0	0.677832	1.259874
LEV	0.000221	0.000652	0.34	0.734	-0.00106	0.001498
_cons	0.70873	0.016184	43.79	0	0.677011	0.740449

Instrumented: LNEG

Instruments: LEV SIZE GROWTH DISSUE TURN CF

Perform test of endogeneity

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = 38.8992 (p = 0.0000)
Wu-Hausman F(1,1840) = 39.6513 (p = 0.0000)

Report first stage regression

First-stage regression summary statistics

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(4,1837)	Prob > F
CF	0.0695	0.0665	0.0695	33.2933	0.000000

Minimum eigenvalue statistic = 27.4413

Ho: Instruments are weak

# of endogenous regressors: 1
# of excluded instruments: 5

	5%	10%	20%	30%
2SLS relative bias	18.37	10.83	6.77	5.25
	10%	15%	20%	25%
2SLS Size of nominal 5% Wald test	26.87	15.09	10.98	8.84
LIML Size of nominal 5% Wald test	4.84	3.56	3.05	2.77

Perform tests of overdentifying restriction

Tests of overidentifying restrictions:

Sargan (score) chi2(4) = 24.5803 (p = 0.0001)
Basmann chi2(4) = 24.8178 (p = 0.0001)

FORM UPR16

Research Ethics Review Checklist

UNIVERSITY OF PORTSMOUTH

<u>Please include this completed form as an appendix to your thesis (see the Research Degrees Operational Handbook for more information</u>

Postgraduate Research Student (PGRS) Information			**Student ID:**	396941
PGRS Name:	Chimonaki Christianna			
Department:	Accounting and Finance department	**First Supervisor:**	Dr. Konstantinos Vergos	
Start Date: (or progression date for Prof Doc students)				
Study Mode and Route:	Part-time ☒ Full-time ☐	MPhil ☐ PhD ☒	MD ☐ Professional Doctorate ☐	

Title of Thesis:	Creative accounting, fraudand IFRS in Greece
Thesis Word Count: (excluding ancillary data)	49070

If you are unsure about any of the following, please contact the local representative on your Faculty Ethics Committee for advice. Please note that it is your responsibility to follow the University's Ethics Policy and any relevant University, academic or professional guidelines in the conduct of your study
Although the Ethics Committee may have given your study a favourable opinion, the final responsibility for the ethical conduct of this work lies with the researcher(s).

UKRIO Finished Research Checklist:
(If you would like to know more about the checklist, please see your Faculty or Departmental Ethics Committee rep or see the online version of the full checklist at: http://www.ukrio.org/what-we-do/code-of-practice-for-research/)

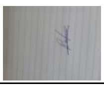
a) Have all of your research and findings been reported accurately, honestly and within a reasonable time frame?	YES ☒ NO ☐
b) Have all contributions to knowledge been acknowledged?	YES ☒ NO ☐
c) Have you complied with all agreements relating to intellectual property, publication and authorship?	YES ☒ NO ☐
d) Has your research data been retained in a secure and accessible form and will it remain so for the required duration?	YES ☒ NO ☐
e) Does your research comply with all legal, ethical, and contractual requirements?	YES ☒ NO ☐

Candidate Statement:

I have considered the ethical dimensions of the above named research project, and have successfully obtained the necessary ethical approval(s)

Ethical review number(s) from Faculty Ethics Committee (or from NRES/SCREC):	

If you have *not* submitted your work for ethical review, and/or you have answered 'No' to one or more of questions a) to e), please explain below why this is so:

Signed *(PGRS)*:		**Date:** 29/12/2018