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CORPORATE FRAUD: AN EMPIRICAL INVESTIGATION OF INTERACTION BETWEEN FRAUD COMMISSION AND DETECTION A DEVELOPING ECONOMY VIEW

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Corporate Fraud: An Empirical Investigation of Fraud Commission and Detection

A Developing Economy View

The aim of this dissertation is to obtain a doctoral (PhD) degree
in the scientific field of "**Business and Management**"

Written by: Rabeea Sadaf .... certified ....

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LIST OF ABBREVIATIONS

AA	Audit Analytics
AAER	Accounting and Auditing Enforcement Release
ACFE	Association of Certified Fraud Examiners
ADT	American Dream Theory
AGM	Annual General Meeting
AICPA	American Institute of Certified Public Accountant
ANNs	Artificial Neural Networks
COSO	Committee of Sponsoring Organization
CPI	Corruption Perception Index
DM	Data Mining
EM	Earning Management
F-Score	Fraud Score
FTT	Fraud Triangle Theory
GAAP	Generally Accepted Accounting Principles
GAO	Government Accountability Office
MD&A	Management Discussion and Analysis
M-Score	Manipulator Score
PCAOB	Public Company Audit Oversight Board
PKR	Pakistani Rupee
PNN	Probabilistic Neural Network
PSX	Pakistan Stock Exchange
SAS	Statement of Auditing Standards
SEC	Securities and Exchange Commission
SECP	Securities and Exchange Commission of Pakistan
SIC	Standard Industrial Classification
SOX	Sarbanes-Oxley Act
TDA	Theory of Differential Association

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INTRODUCTION

The beginning of the twenty-first century witnessed several high-profile corporate fraud scandals in the U.S. and around the world (e.g. Enron and WorldCom, Waste Management, Parmalat, etc.). These failures resulted in a significant amount of loss in the market value. According to a research published by Cornerstone, lawsuits cases registered in the year 2002 alone resulted into a substantial amount of loss in market capitalization; the resulted dollar loss in this year alone amount $203 billion (Qiu, 2009).

However, it is still debatable that whether these failures depict solely the cases of failure in the corporate ethical climate or a general decay in the corporate moral value that gives firms incentive to commit fraud and manipulation (Qiu, 2009). These fraud cases shocked all the market participants created an environment of disbelief by revealing the dysfunctional governance mechanism in the U.S. and got an immediate reaction from regulators (Chidambaran, Kedia, & Prabhala, 2010). The crises in investors' confidence is immediately followed by regulatory reforms and the U.S. congress passed Sarbanes-Oxley Act (SOX) with an aim to regain the investors' confidence in reposting and governance mechanism of firms (Wang, 2013).

Fraud and manipulation, involves intent to deceit, or break the regulatory frameworks to harm the victims (Kassem, 2016b; Wells, 2017). In this dissertation, we follow the definition of fraud and manipulation[1] given by Association of Certified Fraud Examiners (ACFE), *'fraud is the deliberate action or falsification of the material financial facts of an entity committed by intentionally forging or omitting the facts or disclosures in the financial statements to purposefully deceive the users of financial statements'* (ACFE, 2016). *ACFE* categorizes fraud into a) asset misappropriation, b) corruption and c) financial statement fraud. This research is focused mainly on financial statement fraud (ACFE, 2016) for three crucial reasons. First, this type of fraud is most costly, and it caused the highest median loss of millions of dollar in the cases reported in the U.S. alone. Second, the failure of giant corporations has generated a heated debate on the quality of financial disclosure and integrity of reported statement in gaining the trust of market participants, particularly investors (Kassem, 2016b). Third, the cost incurred by this type of fraud goes beyond merely the financial and monetary loss. It could lead to an overall decrease in investors' confidence in

[1]. Throughout this dissertation, the term fraud and manipulation and earning management are used interchangeably. The difference between fraud and earning management is, however, the latter term refers to 'cooking the books' within the umbrella of GAAP (Dechow et al., 2011). The former term, on the other hand, refers to manipulation out of GAAP and allegations by regulators (here SECP).

the audit profession and affects the efficient allocation of resources (Kedia & Philippon, 2009). The loss of jobs and productivity would affect labour market dynamics (Rezaee & Riley, 2010).

In order to deter fraud, it is crucial to understand the causes that motivate managers to commit it. The understanding of the questions: *'what causes managers to manipulate* and *'how best can investors, regulators, analysts and auditors detect manipulation?'* is vital for efficient functionality of capital markets. There would be an increased emphasis of regulators, i.e. SEC to concentrate their investigations on the firms and the sectors that are at high risk of manipulation (Wuerges & Borba, 2010). Despite all the regulatory reforms and efforts by monitory agencies, corporate fraud and manipulation still exist in the U.S. and around the world, and it draws the attention of policymakers and academic researchers (Karpoff, Lee, Koester, & Martin, 2014). Moreover, knowing actual causes of fraud and manipulation is also crucial as there is lack of clarity in predicting that how the regulatory reforms like SOX are effective as a counter-measure strategy to deter frauds in diverse economic conditions that the firms face.

The issues discussed above are hard to address. is due to the fact that the frauds committed are not observable directly; instead, we observe the fraud that has already been detected (G. Chen, Firth, Gao, & Rui, 2006; Poirier, 1980). Meanwhile, the changing environmental influence on how fraud and manipulation are being committed and investigative efforts for detection of manipulation, the one-to-one correspondence between fraud commission and detection is also halted (Qiu, 2009). The vast stream of academic research is focused on the attributes of fraudulent firms. These firms are those who are convicted by enforcement bodies for the confirm manipulation or they have already accepted it publically through restatements or publically disclosed by press or whistle-blowers. (Dechow, Ge, Larson, & Sloan, 2011; Wang, Ashton, & Jaafar, 2019).

The second critical gap identified during in-depth analysis of fraud-related literature is the fact that majority of the fraud-related research is addressing U.S. based firms (Beasley, Carcello, Hermanson, & Neal, 2010; Dechow et al., 2011; Dechow, Ge, & Schrand, 2010; Nigrini, 1996). These researchers rely on the data of Accounting and Auditing Enforcement Release (AAERs) published by SEC detailing the cases of fraud and manipulation. Most of the research stream is directed to these published AAERs firms as a source of test firms, matched to a sample of control firms related to test firms in certain set attributes (Beneish, 1997; Bonner, Palmrose, & Young, 2011; Karpoff, Koester, Lee, & Martin, 2012, 2017; Perols, 2008). Few other researchers focused on the firms listed in developed economies, where they relied on published reports and stock exchange data for obtaining relevant information about convicted firms (Ghafoor, Zainudin, & Mahdzan, 2018; Máté, Sadaf, Tarnóczi, & Fenyves, 2017; Christoph J Skousen & Twedt, 2010; Suhaily Hasnan, Rashidah Abdul Rahman, & Sakthi Mahenthiran, 2014). Meanwhile, the corporate governance practices and regulatory settings vary across countries, significantly affected by the business and legal environment (La Porta, Lopez-de-SIlanes, Shleifer, & Vishny, 1998; La Porta, Lopez- de- Silanes, Shleifer, & Vishny, 2002).

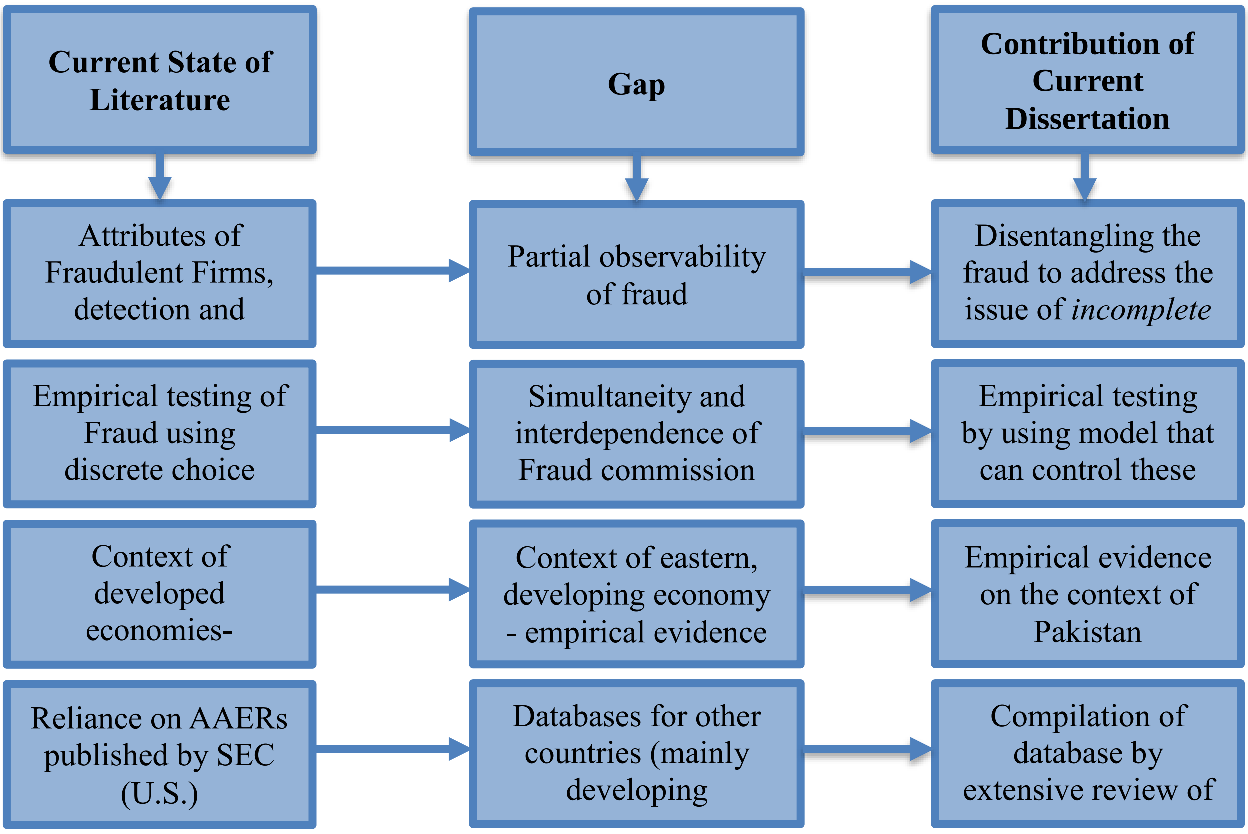

Fig. 1: Gap Analysis
Source: Author's own compilation

Much of the existing streams of fraud-related literature typically rely on detection and deterrence strategies of fraud for the evidence of its existence. An undue emphasis is placed on the role of corporate governance, executive compensation and internal control in deterring frauds and manipulation (Efendi, Srivastava, & Swanson, 2007; H. J. Kim & Yoon, 2008; Magnanelli, 2010; Ocansey & Ganu, 2017; Persons, 2005; Razali & Arshad, 2014; Shi, Connelly, & Hoskisson, 2017; Zhou & Kapoor, 2011). Operationalizing various dimensions of Fraud Triangle Theory, most of the studied literature incorporated discrete choice models, thus ignoring the associated phenomenon of partial observability (Calıyurt & Idowu, 2012; Church, McMillan, & Schneider, 2011; Skousen, Christopher J., Smith & Wright, 2015). There are certain frauds which go undiscovered due to either lack of proper investigative efforts or budget constraint of the regulatory agency. Thus these regulatory bodies consider only those firms which are at the high risk of manipulation or there is public disclosure of fraud (Dechow et al., 2011). A firm that did not face any litigation could be either an honest firm or an undiscovered culprit (Wang, 2013). In all such incidence, discrete choice models would create biased estimate and inferences and conclusions drawn on these results are, therefore, unreliable (Wuerges & Borba, 2010). Previous literature on corporate fraud overlooked the issue of incomplete detection. These studies addressed the frauds that had been detected. Nevertheless, frauds and manipulation include not only the detected cases but undetected frauds as well. As a consequence, these studies understated the actual extent of fraud, which, in turn, introduced farther biases in estimation (Li, 2004).

This study contributes to the literature in several ways. It involves developing a theoretical framework to characterize the consequences and firm-level determinants of fraud and manipulation. The theoretical model is built on an extensive literature review to identify the prevalent gap in the literature. Then, the second part of this study empirically tests the prediction of the theoretical model and assumption. A database is compiled by studying enforcement release issued by Securities and Exchange Commission (SECP) of Pakistan to identify the firms alleged of the manipulation and frauds. SECP, similar to SEC in the U.S, is the regulatory body responsible for monitoring the firms listed in Pakistan Stock Exchange (PSX). Second, this study is based on the contextual contribution to analyze the misreporting firms' financial characteristics in a developing economy. As discussed above, the corporate governance mechanism and regulatory structure in developing markets are widely different from the U.S. (where the majority of fraud-related theoretical and empirical studies are based on the firms in the U.S.). The litigation role of regulators, such as SECP, is very different as compared to the U.S where the major threat of civil litigation exerts a significant impact on the behaviour of the firms. Moreover, the ownership structure and business conditions also have a varying effect depending upon the strength of corporate governance mechanism and right of minority shareholders (Chen et al., 2006).

The significant contribution made by this dissertation is methodological. It fills the existing gap in the literature by addressing the attributes of the firms alleged of manipulation by SECP and firm-level factors that contribute to the detection in manipulation. The major challenge in fraud-related research is the identification issue; we observe the cases of manipulation that have already been detected. It is evident from the discussion that probability that a firm is doing manipulation and probability of observing a firm as a manipulator can be different (Li, 2004). This issue has been addressed in this study by using a statistical model that can control this problem. In this model, the probability of detected manipulation is a product of two probabilities: the probability of fraud/manipulation *commission* and the probability of manipulation *detection* conditional on fraud occurrence. This model is backed by the econometric method to support the latent probabilities discussed in detail in chapter three (Following Wang, 2004). This approach is advantageous in two ways.

a) First, it provides an opportunity to control for the unobserved manipulation (committed but not detected).

b) Second, this model explicitly considers the issue of incomplete detection and the interdependence between the manipulation and detection of manipulation.

This model sets two equations of commission and detection simultaneously to capture the issue of incomplete detection. Previous literature on fraud-related research is lacking in addressing the phenomenon of simultaneity partial detection and simultaneity of manipulation commission and detection, particularly in addressing developing economies. This study fills the literature gap by considering the strategic relationship between the firms' propensity to commit fraud and determinants of manipulation using *bivariate probit estimation* technique.

1. TOPICS AND OBJECTIVES

1.1. Aims of the Research

The primary aim of this study is to focus on financial reporting fraud, which is one of the significant issues affecting the quality of financial reporting. This study aims to highlight the corporate frauds and manipulation in the developing economy setting. This study extends this discussion by highlighting partial observability of frauds (Wang, Winton, & Yu, 2010). An extensive literature review is done to identify the prevalent gap in theoretical and empirical studies of fraud-related research. Moreover, this study comprises empirical testing of models using sophisticated statistical analyses (univariate and multivariate analysis).

1.2. Research Objectives

The primary objective of this study is to analyze firm-level factors that give the managers the incentive to manipulate the financial statements:

1. To determine the relation between M-Score indices and the firm's propensity to manipulate,
2. To examine the characteristics and significance between manipulators and control firms based on M-Score Indices,
3. To examine the firm-level characteristics affecting the firm’s propensity to manipulate
4. To examine the significant factors affecting the detection of manipulation,
5. To examine significant factors disentangling the firm's *propensity to manipulate* from the probability of *detection of manipulation*.

1.3. Research Questions

The above-stated objectives of the dissertation can be translated into the following research question:

1. What is the relationship between the firm's incentive to manipulate and M-Score indices?
2. Are the manipulators and control firms significantly different from each other based on their M-Score indices?
3. What are the firm-level characteristics that affect the firm’s propensity to manipulate?
4. What are the significant factors affecting the detection of manipulation?
5. What are the significant factors disentangling the firm's propensity *to manipulate* from the probability of *detection of manipulation*?

1.4. Structure of the Dissertation

This dissertation is structured as follows:

Chapter one explains research questions, the research objectives and research approach.

Chapter two provides literature review to understand the state of present research related to corporate misconduct in general and financial statement manipulation, in particular. Starting from a general discussion of occupational fraud, more focused operational definitions are provided. This chapter discussed the fraud triangle theory, its development and criticism. Nevertheless, M-Score and other techniques for detecting and deterring manipulation are discussed in details. Finally, hypotheses are deduced based on theoretical and empirical literature.

Chapter three explains the materials and methods used for empirical testing of the data. This chapter highlighted the techniques chosen for identifying firms alleged of misstatements, manipulation and financial reporting frauds. Moreover, a matched sample of control firms is chosen, based on various characteristics. Data collection methods and SIC of manipulators and control firms has been discussed. M-Score analyses and operational definitions of variables are described, including a detail description of sources of data and literature references. This chapter also explains in detail the empirical methodology and estimation techniques chosen for the analyses of data.

Chapter four describes the research findings and their evaluation. At the beginning of the chapter, a general comparison between control and sample firms is presented. Furthermore, the two samples are compared using univariate analysis. Pairwise correlation, time series analysis of manipulators and cross-sectional analyses are done to compare manipulators and control firms. These analyses found empirical support for hypothesis 1. Moreover, a multivariate analysis is performed to compare the indices of M-Score for manipulators and control firms. It leads to conclude the results for the proposed hypothesis H2. In the second stage of multivariate analysis, the issue of partial observability of fraud is addressed using bivariate probit estimation, disentangling the equation for the probability of manipulation and probability of detection of manipulation. The results of these analyses are concluded on the basis of hypothesis 3 and 4. In the third stage of multivariate analysis, robustness of the results is checked. Finally, bivariate probit estimation and simple probit models are compared.

Chapter five delineates the conclusion of the study. Conclusions are drawn from the findings of the analyses presented in chapter four. Furthermore, research implications, limitations and future research directions are also presented in this chapter.

Chapter six presents novel findings of the research and conclude the dissertation.

In the end, bibliographic references and annexures are attached.

1.5. Research Approach

The research approach is a course of action that offers a pathway to conduct research systematically and efficiently. There are three main types of research approaches a) qualitative, b) quantitative and c) mixed methods research (Creswell, 2014). The type of approach chosen for a particular research depends upon the objectives of the research. All the researches must encompass an explicit and disciplined approach to reach the desired goal. This dissertation will rely on a quantitative approach in order to reach the objectives of this study.

In order to meet the objective, a literature review is conducted to understand the prevalent gap and to elaborate 'what is already known' and 'what can be learned'.

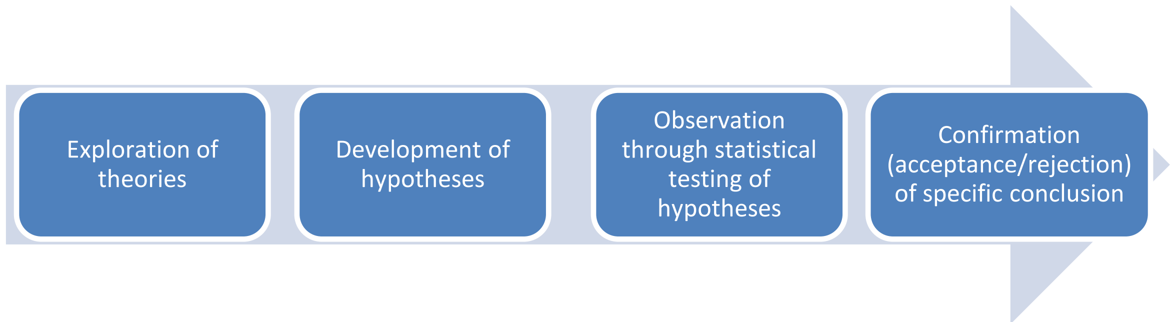

Figure 1-1: Research Approach

Source: (Soiferman, 2010)

A deductive method is applied since this study relied on formulated hypotheses that need to be confirmed or rejected during the research process. Analysing quantitate data with statistical techniques also requires a rigorous understanding of the relationship among variables. A combination of descriptive and inferential statistics is carried out in order to understand the inferences and characteristics of the chosen sample firms. The deductive approach enabled to draw conclusions from generic to specific.

2. Literature Review

2.1. Accounting Manipulation/Frauds- An Overview

The notion of white–collar crime in the literature is attributed to the seminal work of Edward Sutherland who was a criminologist and sociologist in 1940s (Wells, 2017). In his paper on white-collar criminality, he pioneered to integrate economy and crime and used the term *white-collar crime* for the first time (Sutherland, 1940). Comparing white collar criminals with other lower-class criminals, white collar criminal is defined as '*the individuals generally born and raised in good neighborhood, graduating from good colleges, are socially well respected and law-abiding, and typically are forced in to situations of business where criminality is the general way of doing things*'. Contrarily, crimes committed by the lower class include street crimes such as robbery, killing, sexual assault and others *basic crimes* (L. L. Hansen, 2009). Discrediting the conventional theories of crime where poverty, psychological or social status were believed to be causes of criminal intent, the genetic explanation of both white-collar and lower class and street crimes is presented in the *theory of differential association* (TDA). According to TDA, criminal behavior is a learned behavior where frequent contact or social interactions with criminals derive a person into similar behavior (Herman, 1995; Sutherland, 1940). White-collar crimes are real crimes, and as compared to street crimes, effects of white-collar crimes are highly underestimated.

The dictionary definition of white-collar crime is: "crime done by people of high position in the company" (Merriam-Webster). According to this definition, embezzlement is a white-collar crime. These crimes are considered rational and calculated crimes are not merely result of passion. The first (Sutherland's) definition of white-collar crime resulted in different patterns of empirical investigations and criticism too. The resultant stream of literature falls into either 'corporate crime' (Beasley, 1996; Khurana & Raman, 2004; Ocansey & Ganu, 2017; Razali & Arshad, 2014), where researchers focused on the characteristics of organization, or 'occupational crime' (Albrecht, Albrecht, & Albrecht, 2004; Burns & Kedia, 2006; Morales, Gendron, & Guénin-Paracini, 2014; Stanley & DeZoort, 2007), in the characteristics of the perpetrator (Holtfreter, 2005). The initial definition of white-collar crimes came with many unsolved puzzles involving definitional vagueness of this concept (Friedrichs, 1992) since the vast variety of government, occupational and corporate crimes are linked to the conceptual definition of white-collar crimes. Critics argued that this definition is too flexible and diverse. Hence, it should be objectively defined in term of particular discrete actions (Coleman, 1987). Elite deviance, workplace crime and workplace deviance also pose added difficulty of interpretation of initial concept (Friedrichs, 2002).Occupational crime or occupational fraud as defined by the Association of Certified Fraud Examiners (ACFE) is: "*Use of one's occupation for personal gain or enrichment by misusing or misapplying organizational resources* "(ACFE, 2014, p.6). It is one of the primary forms of white-collar crime. In the literature, this term is used as an alternate term to the concepts like *organizational deviance*, *workplace crime*, thus driving it farther from the original concept of Sutherland's white-collar crime. Friedrichs (2002) provided an objective segregation of white-collar, workplace crime and deviant occupational behavior. Occupational deviance is defined as, deviance from professional occupational ethics and norms, like drinking alcohol on the job, sexual offenses etc., while workplace crime includes the common crimes, e.g. rape, assault committed by one at the workplace (Ismaili, 2001).

Friedrichs (2002) defines occupational fraud as; "*In a legitimate occupation, unethical activities that are done by an individual in an attempt to make a personal gain or to avoid personal loss*." Occupational fraud incorporates any fraud committed by employees against the interest of the organization. The perpetrator of occupational fraud could be ranging from general workers, auditors to managers and top executives, where personal gains are valued at the cost of organizational long term interest (Suh, Shim, & Button, 2018). The set of deviant activities could range from petty deviant behavior to large scale sophisticated frauds and misstatements. Bologna (1984) defines corporate fraud as 'acts of fraud or intentional dishonesty, perpetrated by, for or against a business corporation'. The common argument in all types of activities, as listed by ACFE, is:

a) perpetrated in secrecy
b) involve violation of employees' duty to the organization
c) done for personal gain (direct or indirect)
d) can cause damage to organizational resources (both tangible and intangible)

Fraud, according to *Webster's New World Dictionary*, can be defined as, 'intentionally deceiving a person and causing him the loss of property or any other right that he owns lawfully'. In a civil sense, the US Supreme Court defined fraud as 'an act that involves following elements, i.e. material fact, false representation, intent, damage to victim and deception'. The 'intent' of the perpetrator is hard to measure in most court cases (Singleton & Singleton, 2010). ACFE report categorizes the significant types of occupational fraud as

a) Asset misappropriation which includes cash larceny, inventory theft or disbursement fraud committed by either common employee or executive for personal gain.
b) Corruption/ conflict of interest which include action done for personal gain at the expense of organizational interest.
c) Financial statement fraud involves any action to cook the books of a company in such a manner that the resultant statements do not represent the fair value of the company's activity. (Albrecht, Albrecht, Albrecht, & Zimbelman, 2011).

ACFE, one of the most powerful organizations fighting against fraud defines fraud as '*depriving someone of property, legal right or money by intentional deception or using any other unfair mean*'. One of the main objectives of this study is detecting financial statement manipulation/frauds, defined by ACFE as: '*the deliberate action or falsification of the material financial facts of an entity committed by intentionally forging or omitting the facts or disclosures in the financial statements to purposefully deceive the users of financial statements*' (ACFE, 2016).

American Institute of Certified Public Accountant (AICPA) defines financial statement manipulation in Statement of Auditing Standard (SAS 82) as '*deliberate fabrication of fact or omission of concrete disclosure of amount in financial statement for the purpose of deception whereas the resultant statements are not presenting the facts in accordance with Generally Accepted Accounting Principles* (GAAP)' (Karpoff et al., 2017). There is consensus in all above definitions of fraud and mainly financial statement manipulation/frauds that it is *intentional* action committed *deliberately* to harm others for some *personal gain*. Such kinds of frauds are hazardous for market participant owing to the magnitude of harm they cause. Only in the late 90s, the cost born by market actors because of financial statement frauds and manipulation was more than $500 billion (Rezaee, 2002). Although not the typical type of frauds, but the loss incurred by these type of fraud manifolds. According to the recent report of ACFE, the median loss suffered by organizations due to occupational fraud in accounting is about $0.8 million occupying only 10% of global cases reported for this type of fraud. The majority of reported cases fabricated transactions in the accounting system to conceal their unethical act.

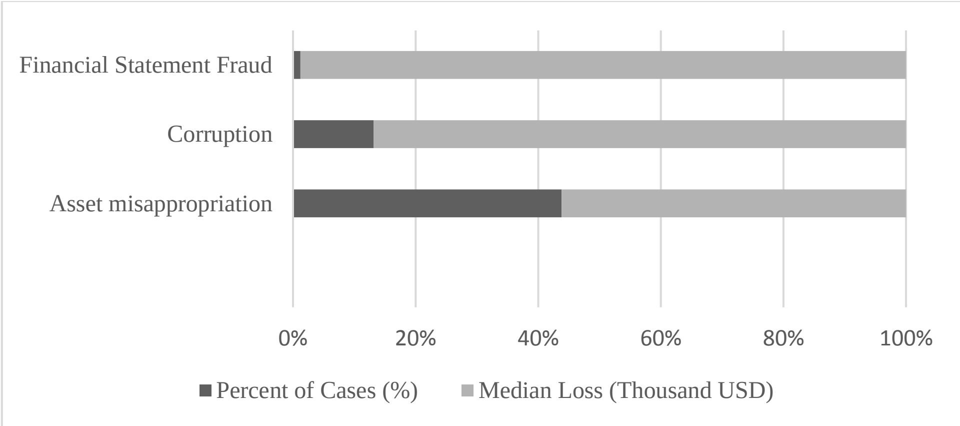

Figure 2-1: Global Study on Occupational Fraud And Abuse (ACFE, 2018)

Fraud tree model of fraud classification (ACFE, 2016; Wells, 2017) identified financial statement fraud and manipulation in the financial numbers could encompass both assets/revenue overstatement and assets/revenue understatement as well. The essential reasons and possible motivations behind these actions, as identified by Wells (2017) could be varied depending upon the prevailing circumstances in organizations. *Overstatement* could be attributed to the following reason (s):

a) Market/analyst expectations
b) Debt covenants
c) Need for debt financing
d) Performance expectations
e) Organizational own performance goals
f) Growth expectation

Contrary to this, *understatement* could be the result of the following reasons:

a) Transfer 'excess' earning to next reporting period, especially when current performance expectation has been achieved
b) Reducing expectations artificially to show an increased growth 'surprise' in the next reporting period
c) To show consistent growth
d) To reduce the value of business purposefully for settlement of other goals
e) To reduce value for planned buyout

During the past three decades, organizations have suffered a million dollar loss due to financial statement fraud and manipulation. Lesser in frequency might be, yet these frauds cause victim organizations either a considerable loss in the form of reputation (Fich &

Shivdasani, 2007) or worst they faced bankruptcy. There is also a loss of public trust in the accounting and auditing profession (Albrecht, 2005). After famous scandal of Enron, American Institute of Certified Public Accountant issued official statement revealing how this scandal has eroded the trust of the public in this profession, consequently giving an irremovable stain to their reputation (Castellano & Melancon, 2002).

Literature has a huge divided opinion on *why* and *how* of financial statement frauds. We can enlist the important contributions made in finding answers to '*why companies commit financial statement fraud.* The important motives include *managerial incentives* (Bergstresser & Philippon, 2006; Burns & Kedia, 2006; Efendi et al., 2007; Rezaee, 2005), *earning expectations* (Burns & Kedia, 2006; Finnerty, Hegde, & Malone, 2016; Kothari, Leone, & Wasley, 2005; Soltani, 2014), *weak insight and governance* (Albrecht et al., 2004; Lin & Wu, 2015; Ocansey & Ganu, 2017; Soltani, 2014; Subramanian, 2015), *earning management for investment goals* (Chu, Dechow, Hui, & Wang, 2018; Linhares, Da Costa, & Beiruth, 2018) and *pressure* (Stein, Charles, & Wang, 2016; Wengler, 2016) etc. To answer *how companies commit financial statement fraud*, we can rely on important contributions made in literature in the domain of *earning management* (Callen, Morel, & Richardson, 2011; Linhares et al., 2018; Nigrini, 2005; Talab, Flayyih, & Ali, 2017), *accruals* (Beneish & Vargus, 2002; Dechow, Ge, & Schrand, 2010; Dechow & Dichev, 2002; Dechow, Ge, Larson, & Sloan, 2011; DeFond, 2010; Kothari et al., 2005), *cooking digits and accounting numbers* (Debreceny & Gray, 2010; Jordan, Clark, & Anderson, 2008; Lin & Wu, 2015) etc. Fraud triangle theory addresses 'Why' of fraud. The dimensions of fraud triangle i.e., opportunity, pressure and rationalization highlight the incentives and motives for doing unethical act and ex-post process of justifying the 'act'. The notion 'how' of fraud deals with methods and techniques that the fraud perpetrator opt for conducting fraudulent act. This involves cooking the books of the firms, either by remaining within the GAAP framework (earning management) or doing manipulation out of the GAAP framework.

2.2 ELEMENTS OF FRAUD

An extensive review of literature helps us identify the following essential elements of fraud (Albrecht et al., 2011; Soltani, 2014).

2.2.1 Overall Ethical Climate

There has been a rise of concern in literature over *how* the ethical climate of an organization can affect the quality of disclosure and other decision choices made by management

(Carpenter & Reimers, 2005). However, it is more rational to consider the ethical climate of the organization as a whole to understand the role of management in financial misconduct and to explore this role in broader.

The spectrum of their overall obligations to general organizational interest (Soltani, 2014). The Sarbanes-Oxley act mandates the public disclosure of organizational ethical code of conduct and compliance of members of the organization to the ethical code of conduct (Martin & Cullen, 2006). Ethical climate in an organization necessitates a strong system of ethical norms embedded in the organization in such a manner that every member of that organization shows a unanimity to his/her perceived organizational ethical climate (Schneider & Reichers, 1983). Ethical climate of an organization is a multidimensional concept, mainly determined by environment, organization type and its history. Victor and Cullen (1988) explained the ethical climate of organization in the light of organization and economic theory and highlighted managerial implications defining its norms and values and guide the decision making in handling ethical dilemmas.

Organizational ethical climate affects the decision making of the management. Numerous studies identified objective financial performance as one of the essential outcomes of the ethical climate of the organization (Newman, Round, Bhattacharya, & Roy, 2017). Several fraud incidents involving external auditors, questions the ethical climate of their organizations- auditors’ perceived ethical climate and the degree to which organizations can endure deviant behavior. Various auditing standards also require auditors to evaluate the management's overall approach towards fraud while conducting the audit. Domino, Wingreen, & Blanton (2015) examined the auditors’ *personal fit* to the organization’s ethical climate and proposed an empirical explanation to auditors’ perceptions about ethical climate and potential fraud risk. The firm’s ethical behavior and attitude toward quality financial disclosure is the main focus for various regulators including the Sarbanes Oxley Act (SOX). Section 406 of SOX requires compliance with the code of ethics for top financial executives. Researchers showed an improvement in the quality of financial disclosure and after the formal adoption of this code (Ahluwalia, Ferrell, Ferrell, & Rittenburg, 2018). The similar argument was extended by Shafer (2015). Conducting a survey study of accountants, he reported a strong relation among perceived ethical climate, social responsibility and accountants' intention towards manipulation of reported earnings. Accountants' attitude toward earning management is significantly affected by the organizational overall ethical climate which defines the perceived ‘tone at the top'. Ethical climate dimension of the organization can also stimulate various other forms of deviant workplace behavior. Peterson (2002) found a strong support for the relation between various types of unethical behavior of employees, i.e. property deviance, production deviance and organizational ethical climate. The ethical culture of an organization also decide the ways employees respond and react to wrongdoings (Buchan, 2005; Casal & Bogui, 2008). Similar argument was corroborated by Kaptein (2011). He examined the relation between employees' reaction to observed misconducts and organizational ethical environment and found a strong support for employees' intended action or inactions and ethical dimensions (both positive and negative).

2.2.2 Tone at the Top Management

Tone at the top can be defined as 'the ways of action a firm's top management assumes its responsibility to set an overall tone of the whole organization (Soltani, 2014). It includes standards of performance, the culture that provides support to the individual's action within the organization, regardless of the written standard of conduct (Transnational Auditors Committee, 2007). This set tone defines and guides the attitudes of employees in the organization. The ways an organization performs, the decision taken by managers and the overall course of action of the organization is built by this specific tone set forth by firm's top management and CEO (Shafer, 2015).

Tone at the top is a multifaceted phenomenon, and there is lack of a well-defined literature especially in financial reporting quality and accounting fraud research. This is probably due to elusive nature of this construct that, it is challenging to measure and analyze the relation between tone at top management and various organizational outcomes (Carpenter & Reimers, 2005). Highlighting the issue of tone at the top for the first time in financial reporting fraud practices, the National Commission on Fraudulent Reporting-Treadway Commission in 1987 presented a structural framework for improving the corporate environment and reporting practices. The commission highlighted the importance of a formal code of corporate governance in setting the appropriate organizational tone. This tone set by top management then creates an environment of control and compliance to rules and regulations, thus leaving a tiny room for falsified financial reporting.

Consequently, the positive managerial tone also promotes the transparency and integrity of financial statements by inserting a system of internal control and intolerance to non-compliance. The guidelines provided by the Commission supported the Committee of Sponsoring Organization (COSO) to propose an internal control framework. COSO highlighted the importance of tone at the top in defining organizational control and overall environment (COSO, 2013). This concept also integrated into the various regulatory framework, e.g. auditing standard and Public Companies Auditing Oversight Board (PCAOB) framework to delineate the significance of tone at the top in defining internal control and organizational environment (Bédard, 2011). COSO report (2010) also heightened the role of the firm's top management, i.e., CEO and CFO in accounting fraud cases. Analyzing Accounting and Auditing Enforcement Release (AAER) cases from 1998 to 2007, 89% of reported cases showed some form of involvement of CEO/CFO in financial misreporting; whereas previous similar report (1999) documented comparatively lesser number of cases where CEO/CFO were held accountable (Beasley et al., 2010).

Literature emphasized the role of top managers and CEO in developing and implementing the overall climate of ethics and strong norms inside the organization (Treviño, Brown, & Hartman, 2003). Thus, the priority of goals of management is a crucial factor in deciding the ethical preferences of middle and lower managers and employees. Prioritizing higher reported earnings and myopic goals of top managers affects the way accountants and managers report earnings and make preferences (Lasakova & Remisova, 2017). Organizational factors are essential in setting a tone at top and employees' perception. Much of the literature in this specific domain highlights the importance of internal control in setting the organizational tone. There is a dearth of mainly empirical literature exploring the link of tone at the top and fraudulent financial reporting (Bédard, 2011). Studies in the literature report a link between the tone of top managers and *fraud risk* (Rubasundram, 2015), since it is essential for auditors to assess overall behavior of management while conducting auditing and fraud risk assessment (Carpenter & Reimers, 2005). Patelli and Pedrini (2015) examined various indicators in CEO letters to determine the leadership qualities and clues of potential earning management using linguistic analysis. They supported the argument of top management ethical consideration being a strong determinant of unethical practices of employees and other managers.

2.2.3 Risk of Fraudulent Financial Statements

One of the most critical components of the Treadway Commission Framework is to comprehend and analyze the firm-specific factors that can cause fraudulent financial reporting and fraud risk (COSO, 2010). The Commission requires firms' top management and board of directors to supervise and monitor the process of financial reporting. The process requires the identification of factors that can risk the integrity of financial reporting.

A higher level of judgement and insight is crucial in entailing the awareness in management for potential fraud activities in order to mitigate fraud risk factors, instead of later designing a distinct effort for handling misstatements. For management, a heightened level of sensitivity and intolerance to financial fraud is inevitable owing to the reputational cost that fraud and manipulation can cause to the organization and its management. Studies reported an enormous cost of building lost reputation and share price loss (Efendi et al., 2007; Lee & Lo, 2016), executive's and top management turnover (Beneish, 1999a; Hennes, Leone, & Miller, 2008) loss of investors' confidence (Beneish & Nichols, 2007) and other legal costs (Karpoff, Lee, & Martin, 2008 a) and a irredeemable damage to society at large caused by misreporting (Zahra, Priem, & Rasheed, 2005).

Lee and Lo (2016) analyzed the impact of the misstatement on the analyst's reputation with the investor and argued that misstatement revelation could affect the reputation of the analyst in the eye of investor and subsequently leads to a loss in trust of analyst skills. Financial reporting fraud has consequences for the labor market too. Researchers agree on the massive loss of jobs for managers and top executives. More than 90% of responsible parties lost their jobs or being fired for their unethical financial reporting (Karpff, Lee, & Martin, 2008). Desai, Hogan, and Wilkins (2006) analyzed the reputational penalty, followed by a misstatement disclosure (violation of GAAP) and management turnover. Moreover, approximately 60% turnover is found in the top managerial position in subsequent violation disclosure. They also reported an inferior status of new employment of these managers and consequent labor market implications. They also faced a significant loss of money due to the restriction imposed on their future investment, fines and penalties and loss in shareholding (Karpff et al., 2008 b). Karpoff et al. (2008) identified 585 companies that were issued enforcement by the Securities and Exchange Commission from 1978 to 2005. They reported more than 37 million median loss for settling lawsuits and an average two weeks loss of suspension of their share trade of stock exchanges. The loss of reputation impairment manifolds all the losses faced by firms for misreporting.

Fraud and manipulation detection and prevention has become a crucial scholarly area for academia and practitioners. The ability of a business to prevent fraud, at first place and to minimize and the loss caused by fraud, supports the firm to gain competitive advantage (Schnatterly, 2003). Firm's strategic decision making and corporate governance practice has a vital role in mitigating fraud risk. Schnatterly (2003) studied the influence of firms' operational governance mechanism on its ability to curtail fraud cost. Offering reforms to the traditional way of governance, they put a measurable framework for operational governance. The operational governance mechanism can also support the company to reduce fraud significantly.

2.2.4 Accountability, Control, Audit and Governance

The recent wave of corporate scandals exposed the significant gap of expectations between managers and other stakeholders, thus resulting into loss of public confidence over the quality of financial reporting, strength of governance and internal control process. The antecedents of these failures, as provided by theoretical and empirical researches, are the lack of internal auditors' expertise and flawed governance processes, the dearth of external auditors and lack of reliability in the process of auditing and managerial malpractices (Reurink, 2016). In finding answers to this criticism, an effective control mechanism, accountability of managers, and well-functioning corporate board is inevitable as suggested by the literature.

Accountability, used in history as an interchangeable term with accounting, is closely related to transparency, responsiveness, equity and fairness (Bovens, 2007). In political literature, it is often described as 'good governance' conduct (Koppell, 2005). It is an evaluation of performance parameters to certain set standards. At the organizational level, accountability refers to a set of perceptions and performance expectations from management, the failure to do so hold them answerable to owners and other stakeholders. It has a direct association with the power, responsibility and compliance. Compliance includes observance to laws and regulations, mainly promoted by legal obligations and also affect the ethical norms and behavioral values of employees and managers (Ahluwalia et al., 2018). In the management misconduct field, SOX has a very prominent role in deriving the firm's ethical financial reporting process. Ahluwalia et al., (2018) conducted a longitudinal analysis of firms to assess their restatement behavior after implementing a formal code of ethics as per SOX legislation. Their findings corroborated the enhanced integrity of financial reporting in the firms having implemented SOX rules.

In finding the relationship between law enforcement, social norms and dishonest corporate dishonest behavior, DeBacker, Heim and Tran (2015) advocated a strong correlation between ethical norms of owners and their tax-avoidance behavior in the US firms. The owners belonging to highly corrupt countries reportedly showed an increased propensity to tax avoidance behavior especially when the size of the firm is smaller. This behavior diminishes with the increase in the size of the firm. Larger companies, mostly exhibit strong internal control, since it provides firms with a stronger fence against frauds and thus supports firms to save costs (COSO, 2013). Studies also gave empirical testing of the relation between a powerful internal control mechanism in larger firms and consequential strong cost of a corrupt act (DeBacker et al., 2015). The results of their study can be explained in terms of separation of ownership and control mechanism as suggested by Berle and Means (1932). They were among the pioneers who suggested segregation of the firm's ownership and control thus uncovering one of the most critical issues of modern corporations (Berle & Means, 1932). Consequently, the issue of conflict of interest ascends thus necessitating a strong need for an internal control mechanism (Soltani, 2014).

Effective internal control mechanism encompasses control over operational activities as well as control over the financial reporting process. Organizational internal control creates an overall environment that facilitates the creation of financial statement, audit control and internal accounting control (COSO, 2013). As defined by COSO's Integrated Framework on Internal Control, '*A firm's internal control environment is a function of organizational structure, management philosophy, style of operation, defining lines of authority and management of personnel*'. In other words, a firm's internal control environment affects the entire process of preparation of financial statements.

Effective auditing mechanism also improves the transparency of financial reporting. A reliable auditing system is unquestionable in improving the quality of financial reporting. Many studies found the relation between financial reporting quality and auditing firm's tenure (Stanley & DeZoort, 2007), auditor's independence (Soltani, 2007), auditors' incentives (Krakar & Žgela, 2009), audit-firm expertise. (Lin & Hwang, 2010), and audit fee (Kannan, Skantz, & Higgs, 2014).

In some cases, auditors are doing 'impression management' for their client. Hence auditors act more like a business advisor than auditor (Albrecht et al., 2011). Tang, Chen, & Lin (2016) created a comprehensive index for measuring financial reporting quality using both auditing and accounting variables to perform a cross-country analysis. The strong legal enforcement systems of the countries with developed capital markets have enhanced financial reporting quality. The overall ethical climate of a country also affects the quality of financial disclosure. Most countries having lower rank (highly corrupt) in the Corruption Perception Index (CPI) have low-quality accounting and legal system (Kimbro, 2002). Kimbro found a strong argument for the relation between a country's legislation, accounting system, number of accountants and perceived corruption level. He also stated that countries with an improved accounting system, a better legal environment, and a higher number of accountants are least corrupt. Malagueno, Albrecht, Ainge and Stephens (2010) reported that accounting and auditing environment of a country shaped by perceived corruption of the country. Using a cross-country sample, they found strong empirical evidence for the support of this relation using different models.

The concepts of accountability, control, audit and governance are interlinked and can be aligned to the broader function of the firm's corporate governance environment. Corporate governance is actually '*a monitoring tool of the firm for assessment of liability and answerability of managers through the board of directors, audit committee and other control mechanism'*. The three core principles of corporate governance are; a) transparency, b) competence and integrity and c) effective monitoring system (Rezaee & Riley, 2010). Governance mechanism of the firm, on the one hand, safeguards the efficient use of resources of the firm in the best interest of stakeholders and at the same time acts as a watchdog to incorporate effective accountability mechanism for the stewards of resources (Magnanelli, 2010). A need for a well-established mechanism to integrate accounting and auditing with performance goals, public accountability, governance, ethics and society as a whole (Zadek, 1998). Various regulatory reforms and institutions are evolving to regulate the practice for financial reporting of firms.

The concept of external monitoring and public governance also has a direct linkage to the way organizations are managed and controlled and subsequent disclosure practices and other corporate decisions (Beck, Demirgüç-Kunt, & Levine, 2002; La Porta, Lopez-de-Silanes, & Vishny, 1998; La Porta, Lopez-de-Silanes, Shleifer, & Vishny, 1997). The countries' overall legal environment contours the corporate ethical environment and financial reporting practice. Zhang (2018) reported a noticeable decrease in fraudulent financial reporting practices in firms (issued enforcement action) in *post regulatory reforms era* in China due to enhanced monitoring and governance. Moreover, stronger institutional environment and stricter regulations can inhibit unethical practices and fraud.

2.2.5 Personal Interest and Executive Compensation

One of the essential elements of fraud is inappropriate CEO incentives and compensation packages (Efendi et al., 2007). This issue is being debated in corporate finance and corporate governance (Hillman & Dalziel, 2003; Mehran, 1995) to find a link between executives personal interests/motives and firm performance (Aggarwal & Samwick, 2006; Mehran, 1995), quality of financial reporting (Albrecht et al., 2004; Conyon & He, 2016; Watrin & Ullmann, 2012) and fraud risk analysis (Wengler, 2016). Executive compensation and its link to performance is an important issue due to the lack of appropriate measurement standard of the firm's performance and executive compensation (Aggarwal & Samwick, 2006). Owing to the significance of compensation structure of executives in understanding fraud risk and misstatement, auditing standard (A.S. No. 18) issued by PCAOB entails auditors of public companies to understand compensation arrangement of CEO in client firm as it can lead to 'pressure' on management for keeping earning higher (Wengler, 2016). Literature offers an empirical consensus on the requirement of auditors to consider executive compensation pattern due to potential fraud risk associated with executive equity compensation (Kannan et al., 2014).

Most of the fraudulent companies offer their CEOs thousands of dollars as compensation packages and endowments in the form of stock options. This causes management to manage stock price higher at any cost (sometimes at the expense of financial reporting precision) (Bergstresser & Philippon, 2006). There would shift in CEOs' motive and attention from managing firm and achieving its long term goals to managing the stock price only (Albrecht et al., 2011). The motivation of fraud has a direct connection with the CEO's misplaced incentives. Literature has mixed evidence on how CEO equity investment would affect his/ her incentive to misreport financial information. Studies show that the firms where executive compensation is in the form of stock options have increased the probability of fraud and misreporting of firms' financial performance. Management literature till date confirms the relation of CEO stock option and the tendency of financial malfeasance (Ndofor, Wesley, & Priem, 2015), yet studies are demonstrating little or no empirical evidence of relation (Armstrong, Jagolinzer, & Larcker, 2010). Though CEO equity investment can support the firm to curb agency issue, yet deciding executive compensation is a crucial task for investors since it can cause a perversion in managerial view of their responsibilities towards the organization and its shareholder. Offering a simulation model for the optimal level of managerial compensation to reduce fraud probability, Andergassen (2008) provided a trade-off model for the benefits of managerial stock option and cost of fraudulent behavior.

Managers of a company are similar to rational economic actors striving to maximize their wealth. The behavior, norms and ethical consideration of management is a crucial factor in defining their 'self-interest' motive. Studies on recent financial fraud corroborate an overall decline in morality and ethics of individual in past decades no matter what is our measure of ethics or behavioral integrity (Albrecht et al., 2011). Literature also linked unethical managerial behavior and self-interest to ‘egoism' self-serving attribution and narcissism to managerial motives of fraudulent financial statement (Rijsenbilt & Commandeur, 2013; Schrand & Zechman, 2012; Soltani, 2014). Rijsenbil and Commandeur built a scale to measure CEO narcissism and potential fraud threat to the organization and found a positive relation between them. Narcissist behavior force CEOs to undertake decision, for self-praise, that could be detrimental to the organization's long term objective (Harrison & Fiet, 1999).

2.2.6 Pressure

External pressure is one of the essential motives identified in the literature for intentional fraudulent reporting in firms and manipulations. Firms with alleged fraudulent reporting have a considerable amount of external debts. Fraudulent reporting is more evident in the firms with comparatively stricter debt agreements and requirements for creditors. Hence, it can be used a potential red-flag for auditors’ fraud risk analysis (Church, McMillan, & Schneider, 2001). The external debt exerts massive pressure on management to report a *higher-than-actual* income to offset the requirements of interest payment and other requirements of creditors (Albrecht et al., 2011). The desire of a firm to attract external financing at low cost is one of the major motivations behind earning management practices. Scholarly literature supports the ‘debt-hypothesis' of earnings manipulation. Dechow, Sloan, & Sweeney (1996) analyzed firms subjected to enforcement action by SEC for violating GAAP using a decade of data from 1982-1992 and found that firm's goal of attaining external financing at optimal terms is the primary motive behind misstatements.

Consequently, the reported firms also encountered a substantial increase in the amount of cost of capital upon the revelation of manipulation. Financial distress and possible proximity to failure is an essential determinant of financial misreporting. Firms near to failing, are more likely to mask their fragile financial position and are more prone to fraudulent financial reporting (Rosner, 2003).

The unrealistic earning goals of firms, developed by the pressure of investor and analyst expectations, create a desire in firms to meet those goals by cooking the books. Empirical studies on the antecedents of fraudulent firm’s behavior confirms *analyst expectation* as one of important driver for alleged misreporting (Bagnoli, Beneish, & Watts, 1999; Efendi et al., 2007). The situation is worsened by *peer pressure* earning per share figure. Mostly fraudulent companies lack managerial judgement rely heavily on the stock process of other firms in the industry as a matric of performance comparison (Albrecht, 2005). Firms inflate earnings fraudulently to meet analyst expectations of performance and to beat peers in the industry in terms of reported earnings-per-share (EPS) performance (Wood, 2017). Consequently, higher-than-expected earning can trigger the auditors for fraud risk analysis.

The unethical actions of firms are also affected by *the economic boom* of the late '90s and early '20s where major business corporations showed massive growth in profitability. New business models, globalization and economic conditions forced firms to maintain a growing reported income results. There was a significant gap between book value and market value of the firm's capitalization thus signaling financial malfeasance (Soltani, 2007). The nature of *flexibility* offered by GAAP also helped the firm to manipulate the figures under the ethical umbrella of rules, thus exploiting the loopholes offered by rule-based nature of GAAP.

2.3 Theory and Theorizing

The foundation ground to fraud literature dates back to the work of Sutherland who is credited for the use of term white-collar crime for the first time and gave new directions to criminology research integrating economics and criminology theory. Contrary to widely-held believes that poverty is the main cause of crime, he described white-collar criminals as sophisticated professionals who are using their professional status and generally act as 'trust breakers'(Sutherland, 1940). Sutherland believes that white-collar criminals punished lesser than other violators. The reasons, he described, as 'fear', 'praise', a lesser degree of criminal charges and lesser penalties imposed (due to their higher position) and a wider 'spread' of the consequences of their crime diffused through longer time span makes white-collar criminals different from other violators (Dorminey, Fleming, Kranacher, & Riley, 2012).

Modern fraud theory[2] originated from the efforts of Donald R. Cressey, a former PhD student of Sutherland who worked on embezzlement behavior. He interviewed (after granted necessary permission) prisoner inmates convicted for embezzling the funds and described those offenders as 'trust-violators'. He, then, proposed a classical model elucidating the individual's psychological factors that 'must be' present for any fraud to occur (Cressey, 1953). These factors are:

a) perceived pressure,

b) perceived opportunity and c) rationalization.

[2] Originally this theory, has a basis in sociology literature, is adopted, adapted, modified and tested in accounting and forensic fraud literature successfully for more than six decades (Van Akkeren & Buckby, 2017).

Perceived pressure is described by Cressey as '*non-shareable financial problem or need*, whereas perceived opportunity '*knowledge and position to commit a crime'* and rationalization as '*self-ability to satisfy one's inner-self*''. *Cressey* describes pressure (perceived) as 'non-shareable financial problem' than a simple economic motive. This view is supported by Albrecht (2005) who noted that pressure could result from both financial needs, e.g. external debt as well as non-financial motives. Examples include a desire to show *better than actual performance,* work-related stress and *ego* can be non-financial pressure resulting in the fraudulent act (Albrecht, 2005). The pressure may or may not be actual pressure, rather a *perceived pressure* for an individual that can no longer be a certain *pressure* for another individual in the same situation (Albrecht, Albrecht, & Albrecht, 2008). Economic loss, worsen sales volume, inability to meet analysts' expectations and peer group performance pressure can create a motive for financial manipulation in the company.

Opportunity (perceived) includes the perception that there is a weakness in the internal control system. Executives who believe that they can commit and conceal fraud with a lesser degree of probability of being caught push them into fraudulent act.

Contrary to these, the cases where executives fear they could be caught (robust internal control and governance mechanism) seldom do fraudulent act despite enormous pressure (Albrecht et al., 2008).

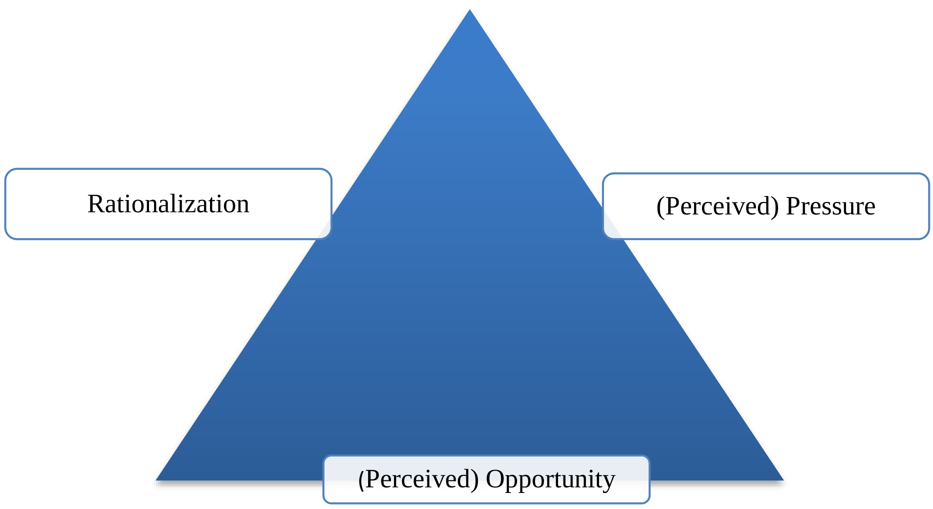

Figure 2-2: Fraud Triangle

Source: author's compilation based on (Wells, 2017)

Rationalization involves finding ways to vindicate the act. Cressey believed that most embezzlers are *first-time offenders* who believe themselves common, law-abiding people, forced into criminal behavior due to the unforeseeable situation. This allows them to justify acts, reducing *cognitive dissonance*[3] (Ramamoorti, 2008). In an effort to remain in their 'comfort zone' fraud perpetrators have to justify their actions since they think themselves a particular dilemma where situation left them with no other options except to commit the fraudulent act (Cressey, 1953).

2.3.1 Developments in the Fraud Theory

Cressey developed three factors forcing individuals into the fraudulent act (a classical model for occupational fraud research), but never used the term 'Fraud Triangle. Joseph Wells (Wells, 1985) was the first person who used these elements in the form of a triangle in his video presentation about Cressey. His action led to what we know presently *a fraud triangle* (Morales et al., 2014), referred in the theoretical and empirical literature of corporate misconduct for more than three decades. Since 1985, various developments in the basic fraud theory have been the insertion of the three elements on the points of the triangle, on the sides of the triangle and/or formation of a three-dimensional pyramid form of the triangle, yet, there has been no change in functionality of the elements (Denis, 2017). Hollinger and Clark in their book, 'Theft by Employees', presented a different model for understanding individual fraud motives as described by Cressey. They proposed interrelated causes of deviant behavior and theft include a) non-shareable financial pressure, b) younger employees are lazy-not willing to work hard, c) dishonesty and greed d) job dissatisfaction and e) shared norms (Hollinger & Clark, 1983). Their study summarizes employees' deviance is a result of their job dissatisfaction. Their finding leads to conclude that: a) Income level or poverty is not the cause of theft. Employees of any income level can commit it. b) There is a strong relationship between employees' dissatisfaction and deviant behavior. c) Internal control or perceived internal control can help firms to reduce deviance.

Albrecht with his colleague developed a *Fraud Scale* in their book 'Deterring Fraud: Internal Auditor's Perspective' and conducted interview of the internal auditors from 212 fraudulent companies. Fraud scale consists of three components; two of them are the same as in the initial fraud triangle, i.e., opportunity and pressure. The third component, rationalization is

[3]. This theory holds the view that human beings are very sensitive to the harmony in their actions and believes (cognitions). Recognizing any disharmony will result in dissonance, subsequently leading into an effort to find ways to reduce it. Hence three basic ways to avoid dissonance include; change of belief, change of action and change in perception about action (Festinger, 1957).

modified and replaced by *personal integrity*. *Personal integrity* is defined as ‘personal code of conduct adopted by each individual, determining his honesty or dishonesty’ (Albrecht, Romney, & Howe, 1984). The higher pressure and opportunity with lower personal integrity lead an individual to commit a fraudulent act, and the opposite is true otherwise. Apparently simple, but the criteria for analyzing one's integrity is very difficult to operationalize. Taking fraud perpetrators as a group enhances added difficulty to the prediction of fraud. For fraud scale, Albrecht et al. (1984) analyzed a large data to propose a comprehensive list of the potential *‘red flags’*; risk factors indicating potential fraud. Dorminey et. al. (2012) argued that personal integrity is manifested from past decisions of individual and decision-making process too. An individual with greater personal integrity is less likely to rationalize the fraudulent behavior (Lokanan, 2018). Albrecht (2005) noted that the high personal integrity of employees, determined by the embeddedness of religious orientation, would be less unethical.

Notwithstanding the amount of pressure and opportunity, higher personal integrity (being religious) overshadows all other factors (Albrecht, 2005). A revision to the initial fraud triangle was presented by Wolfe and Hermanson (2004) thus offering deeper insights into fraud detection and prevention. They argued that the fraud triangle would be enhanced and improved by considering forth element ‘*capability*', thus converting the initial model into a four-sided ‘*Fraud Diamond*’. They emphasized that the presence of necessary individual skills and ability is requisite, along with the other three elements, for a fraud to occur.

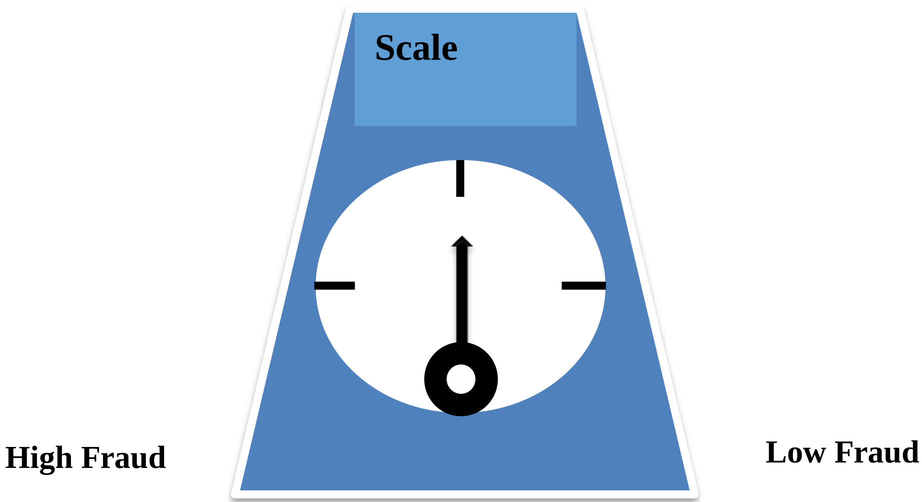

Figure 2-4: Fraud Scale
Source: author’s compilation based on (Albrecht et al., 1984)

The opportunity offers a doorway, pressure and rationalization derives a person, but the necessary ‘capability' to recognize the opportunity, to take its advantage and walk through the doorway, is necessary for a fraud (Wolfe & Hermanson, 2004).

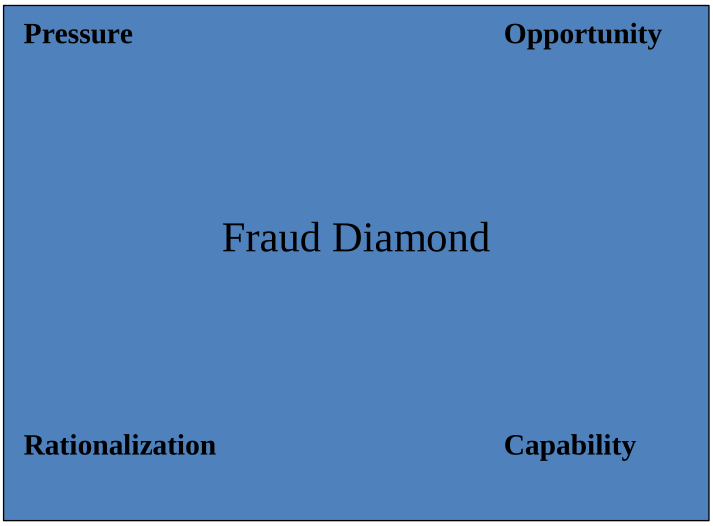

Figure 2-5: Fraud Diamond

Source:(Wolfe & Hermanson, 2004)

Fraud diamond brings modifications to the *opportunity* leg of initial fraud triangle because *capability* enables executives and employees to identify and exploit the weaknesses in the internal control system. Thus this model is restricting the available opportunity to a limited proportion of individuals who have required skills to convert opportunity into fraud act

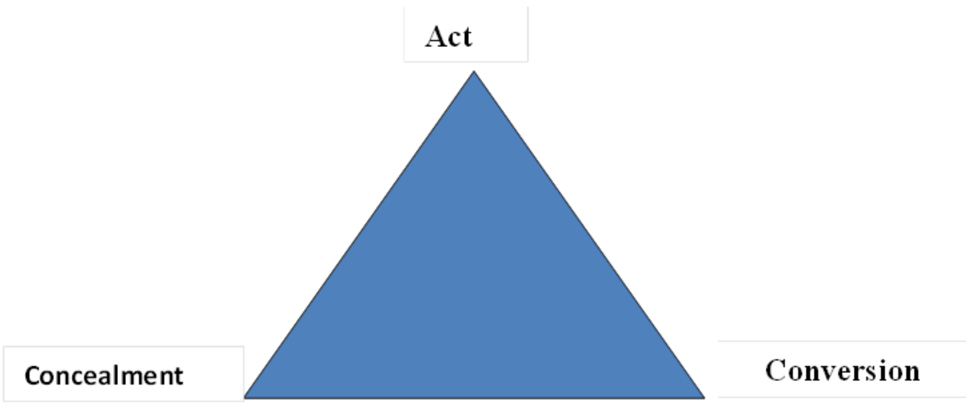

Figure 2-6: Triangle of Fraudulent Action

Source:(Kranacher, Riley, & Wells, 2011)

(Dorminey et al., 2012).While fraud triangle explain individual factors that can derive an individual (actor) for fraudulent behavior, researchers proposed a triangle explaining the process of *fraudulent action* (Albrecht et al., 2011; Kranacher, Riley, & Wells, 2011; Ramamoorti, 2008). Meanwhile others entitled it as a *triangle of fraudulent action* (Dorminey et al., 2012) or elements of fraud action (Albrecht et al., 2008). The three legs of this triangle are *act*, *concealment* and *conversion* (Trompeter, Carpenter, Desai, Jones, & Riley, 2013).

This triangle supports fraud investigator and forensic auditors to understand and unveil how fraudulent act perpetrated, what arrangements were made by the perpetrator to cover it from external auditors, and into what forms, it is converted to benefit the perpetrator unlawfully. The precedence of this triangle over previous fraud triangle is the ease with which its elements can be operationalized and measured. Researcher agreed on the difficulty of measuring the *intent* which adds complexity to the process of fraud investigation.

The difference between accidental error and intentional manipulation/fraud is the presence of *inten*t, especially *evidence of intent*. *Triangle of fraud action* supports the investigators to overcome this difficulty. The fact that the perpetrator had committed the act, concealed his act (fake documents) and converted the act to get some personal gain, makes it almost impossible for perpetrator to negate his *intent* or to claim he meant no harm (Kranacher et al., 2011). The proof of concealment explicitly affirms that *act* and *conversion* were done intentionally, and makes the investigation of the fraud process straightforward.

Several researchers put their efforts to extend the theory of fraud and develop a new model that can explain the diverse nature of occupational fraud. Kranacher et al. (2011) offered an acronym, *M.I.C.E.*, to explain the rationale behind manipulator's unethical behavior beyond the explanations offered by fraud triangle theory. M.I.C.E. model stands for money, ideology, coercion and ego or entitlement, thus expanded the pressure side of the initial fraud model. *Money* and *ego* (entitlement) offer common explanations for the motives behind the fraud. People make unethical choices when they are carried away with their economic goals. Similarly, the ego can drive an employee to a fraudulent act especially when he is more fretful for his reputation and status. *Ideology* and coercion are challenging to identify and measure.

Ideology explicates the cases where intentions behind fraud involve some ideological motive that is expected to bring good to others. Various situations where ideology can be understood as a motivator for unethical act include tax evasion, e.g. fraudster believes that 'tax is unjustified'. Various examples involve the ideological perception of a fraudster to help, e.g., needy people or assisting terrorist organization due to his perceived philosophical stimulus. *Coercion* explains the situation where the perpetrator is forced into a situation to commit fraud without willingness (Kassem & Higson, 2012). Coercion can be demonstrated as 'obedience' to the authority. Many corporate scandals of the past showed the situation where a subordinate (accountant or other lower level employee) is managed by fear or intimidation for an immoral act. Obedience and coercion are grounded on a strong moral foundation (Murphy & Dacin, 2011).

Kassem and Higson (2012) noted the inherent complexity in the notion of frauds due to their diverse nature and the complication in understanding the motives behind frauds. It is challenging for external auditors and fraud examiners to understand; a) nature of motivators, b) the way perpetrator carries out fraudulent activity and c) the channels through which he conceals or converts his action into legitimate forms, for the assurance of not being caught. They offered an integrated framework for external an auditor that encompasses all previously discussed fraud models and their extensions since they are critical to understand the complex picture of corporate fraud. The first fraud theoretical framework explicitly highlights the importance of factors highlighted by extensive literature of fraud theory (capability, integrity, ego, coercion, ideology), and enables external auditors to better understand the phenomenon of corporate fraud (Kassem & Higson, 2012).

One of the important essential components of Cressey's fraud triangle theory is a 'non-shareable problem' that can lead, otherwise trustworthy individuals to commit fraud. The initial argument of non-shareable nature of financial goals generated huge debate and criticism in literature since it presents a myopic view of fraud: '*an individual acting alone for some financial goals'* (Dorminey et al., 2012; Lokanan, 2018). Contrarily the major fraud cases reported at the beginning of 21st century substantiate the group actions or 'management collusion' as the primary factor behind the act (Albrecht, 2005; Morales et al., 2014; Cumming, Dannhauser, & Johan, 2015; ACFE, 2016). *Collusion is a non-formal agreement between two or more than two parties with an intention of carrying deceitful action to harm a third part purposefully*. It, consequently, weakens the accountability, and makes organizations more fragile by jeopardizing internal control (COSO, 2013). Collusion can be the result of an alliance of employees of one or from multiple organizations thus exacerbating the complexity in the process of fraud examination and control.

Vousinas (2018) presented a *fraud hexagonal model* by presenting an acronym S.C.C.O.R.E (Vousinas, 2018). Five of six components of S.C.C.O.R.E. model are derived from previous models (**s**timulus/pressure, **c**apability, **o**pportunity, **r**ationalization and **e**go), the sixth additional element '**c**ollusion' is proposed to present an extended framework for the situation where collusion is a fundamental constituent of corporate fraud. ACFE (2016) highlighted that more than half of the reported fraud cases are the results of collusion between several individuals perpetrating fraud as a shared deed, causing median damage of $0.6 million to the victim organizations (ACFE, 2016).

The fraud triangle is criticized for its too individualistic nature, which is not valid in most of the fraud cases. Ramamoorti and other co-authors challenged the 'non-shareable pressure' argument of Cressey and presented *A.B.C. model* of fraud, incorporating the behavioral element in fraud theory (Ramamoorti, Morrison, Koletar, & Pope, 2009). The three sides of the fraud triangle can be better understood by considering the element of behavior. The element of 'rationalization' itself has roots in psychology (attempt to neutralize inner voice by justifying illegal act). The other elements i.e., *opportunity* and *pressure* are much likely built on psychological perceptions of the perpetrator (perceptions of not being caught, perceived pressure to show better than expected results). A.B.C. model (*A bad apple, a bad bushel, a bad crop*) extends *the individual* view of frauds (A bad apple), presented by Cressey, by offering additional insights about managerial collusion (A bad Bushel) and *a bad crop;* when unethical culture penetrates throughout the organization. *A bad crop* breeds as a result of subsequent failure of top management to proactively curb *a bad apple* (individual fraudster) colliding and affecting other employees to form *a bad bushel* and failure to set and implement internal control and ethical tone at the top.

Cressey's description implicates *fraudster* as a 'trust violator carried away with temptations, otherwise ethical and law-abiding rational individual. All three sides of the triangle are not crucial factors for any fraud event to occur. Schuchter and Levi (2016) modified the fraud triangle by adding '*inner voice*' in place of rationalization and noted that inner voice is an essential factor for inhibiting a first-time fraudster from committing the unethical act. Rationalization, is the ex-post element, can be better understood as a *relief effort* that fraudster does in an attempt to overcome cognitive dissonance. This inner voice becomes silent when unethical action is repeated again and again (Ramamoorti et al., 2009).

Notwithstanding, rationalization no longer remains an essential element in the fraud triangle. Dorminey et al. (2012) presented a triangle of fraud by offering a distinction between accidental, first-time fraudster from habitual fraudster or *predator*. They argued that the first time offender manages earning or cooks the book due to some perceived pressure. Later, he adopts this habit and rationalization does not remain an important element for fraud triangle. Fraud triangle is explaining predator's action that does not need an element of pressure and rationalization; only an opportunity can suffice to lead predator's action. The elements of this new fraud triangle include an *arrogant* individual, with *the criminal approach*, and an *opportunity* (Dorminey et al., 2012).

2.3.2 Criticism on Fraud Theory

Fraud triangle theory laid the foundation of corporate fraud theory and has become a theoretical base for linking criminology and economics. This theory has successfully incorporated into the framework of accounting regulations and professionals. The first support for this theory came from Joseph T Well, founder of ACFE. They made this theory as an empirical explanation to corporate fraud and manipulation, thus converting initial *embezzlement hypothesis* into a robust theoretical base from which 30 years of theoretical and empirical literature emerged. Support for this theory also came from audit professionals and regulators, e.g. the American Institute of Certified Public Accountant (AICPA), in SAS 99, and Public Company Audit Oversight Board (PCAOB) who instigated fraud triangle in their *guidelines for fraud risk analysis* and for conducting fraud audit and investigation (Donegan & Ganon, 2008). SAS 99 entails auditors to contemplate the elements of *pressure*, *opportunity* and *attitude* thus encouraging mono-dimensional explanation of fraud risk assessment in its guidelines (Trompeter et al., 2013). Notwithstanding all the support that received from professionals, standard setters and academicians, this theory has received much criticism both from criminologists and researchers in business ethics. The major criticism is directed toward the professionals who blatantly incorporated this theory as the general theory of corporate crime without considering the other theoretical perceptions of financial fraud (Langton & Piquero, 2007).

The fraud triangle is also questioned as the general theory of corporate crime in highlighting the motivations or elements leading an individual to the criminal act. This theory should be interpreted cautiously since Cressey did nothing about *corporate fraud* (Denis, 2017). The three sides of the triangle, as explained, are the elements that should be present during an embezzlement act. Generalizing embezzlement theory as the theory of financial crime is misleading owing to its narrowly-focused narrative. Denis (2017) offered a critical investigation of the geometrical shape of the initial theory and its extension and argued that practitioners and regulators should observe extreme care in generalizing this theory since there are corporate frauds in a multi-dimensional construct. The three-element interpretation of diverse financial fraud is also criticized by Lokanan (2017) because fraud is a multi-dimensional phenomenon, and the ACFE framework offered by ACFE and standard setters is a biased interpretation of, actual an n-dimensional concept (M. E. Lokanan, 2015).

The fraud triangle is too restrictive as it considers the problem of individual perpetrator acting alone for some personal financial motive using his status or position. This view denotes ‘fraud' as an individual phenomenon, offering explanations to individual perception of the problem, opportunity and rationale behind that motive, thus ignoring other interpretations of white-collar crime (Lokanan, 2015). In its inception, FTT is presented as *elements* offering explanations about embezzlement behavior, therefore it should not be recognized as a general theory of financial crime (Donegan & Ganon, 2008).

Fraud triangle has its roots in other social sciences (behavior and psychology) which add to the difficulty in its acceptance as a general financial crime theory. The element of rationalization is not quantifiable, a weakness of the fraud triangle acknowledged by SAS 99 (Skousen, Christopher J., Smith & Wright, 2015). The consideration of *individual only* interpretations of white-collar crime without seeing social interactions and ethical climate makes the process of fraud detection and deterrence hard and ineffective. The element of rationalization in the fraud triangle poorly presented since it is a significant factor for the first-time offender only (those who are otherwise trustworthy). They need to justify their act to avoid moral discomfort which is not essential for predators. Fraud triangle fails to incorporate the behavior of routine perpetrators who do not need to justify their actions to themselves and others (Ramamoorti, 2008). Rationalization is the ex-post element of fraud and can be related to other elements after the act is perpetrated (Murphy, 2012).

Fraud triangle presents the individual as a solo player, acting alone for overcoming pressure created by a non-shareable problem (Cressey, 1953). Nevertheless, the incidents of corporate fraud reported at the beginning of this century disregarded this claim. High-level fraud is typically a team effort (Ramamoorti, 2008). Major collapses of Enron, WorldCom were a result of managerial collusion or control override (Dorminey et al., 2012; Free, 2015). Researchers also highlighted the shortcoming of fraud theory in explaining co-offending.

Collusion or co-offending has its ground in *differential association theory*: dishonesty can be learned from interacting with dishonest individual or group. Impersonal and interpersonal interaction of fraudster can form a basis for co-offending (Van Akkeren & Buckby, 2017).

Fraud triangle fails to incorporate societal context, which forms the basis of individual behavior. The individual-centric focus of the fraud triangle presents fraud as an individual action without elaborating its symbiosis with the external environment that is shaping an individual's behavior. Researchers also criticized its inability to address diverse institutional settings. Focusing merely on U.S ideology where money, coercion and ego can be driving factors for the fraudulent act. This theory cannot be successfully incorporated in its original form to address diverse cultural and societal forces that are varied in their perceptions about motivation, opportunity and morality (Cieslewicz, 2012). This concept is further elaborated by *the American Dream Theory* (ADT) of corporate fraud. According to ADT, the quest of economic well-being and 'more money', as the dominating factors for interpreting corporate misconduct, it may no longer be useful in explaining the motivation of fraudster in another country setting. An excessive emphasis on monetary success can drive corporate executives to the situations where they exploit the opportunities, possibly when there is weak internal control, and justify their actions. Justifications of financial fraud for personal gain is relatively easier in societies which are overly ambitious for success (money by 'any means') (Choo & Tan, 2007).

Financial frauds can be explicitly understood by taking into account the notion of general deviant behavior or antisocial attitude associated with them (Morales et al., 2014). A person committing any financial crime, i.e., asset misappropriation, financial statement manipulation, earning management, or unfair executive compensation breaks the law or violates trust. This notion is widely criticized in the literature, since defining 'what is fraudulent' is itself subjective in its nature as it can lead to ambiguity; person abiding law of one group might be breaking the rule of another. A mid-level accountant in Enron confessed later that she was coerced to manipulate the figures by higher authorities. She was abiding by the rule of one group, ended into a deviant behavior by breaking rules of accounting and auditing. A proper definition of 'what is the rule?' and 'what is deviant behavior or financial fraud?'' involves a big picture- a socio-political view of fraud, deviant behavior and law, accepted by a large group (Becker, 1963). Brecker's notion of fraud does not include personality traits of the fraudster (ego), economic situation (pressure, monetary success) which formulate the basis of fraud theory. Instead, fraud is defined as a deviation to the rule of law, violation of rules that society considers appropriate.

Criticizing Cressey for offering a restrictive view of fraud or embezzlement, where a fraudulent act is committed when a person experiences a pressure, feasible conditions and justifications of act, Morales et al. (2014) pointed out the limitations of Cressey's model in providing sociological interpretations of fraud. Putting general fraud theory based on *individual only* explanation provides a biased view of fraud (Berger, 2011). Berger (2011) provided a comprehensive discussion on white collar crimes, as '*the abuse of corporate and government power'*. Contrary to the previously held theoretical and empirical explanation of white-collar crime (the act of an individual), he provided an extended discussion, incorporating organizational internal environment (which calls 'micro-sociological) and external macro (which calls 'macro-sociological) factors (Free, 2012).

Advancement in the literature on fraud theory resulted in different theoretical explanations of fraud, broadening its micro, perpetrator-centric focus to elaborate macro-level reasoning of fraud, encompassing environment which can affect occurrence or non-occurrence of fraud. The macro-view is believed to be more authentic in understanding perpetrator's motivation and designing deterrence and control (Mailley, 2015). Literature has a dearth of theoretical and empirical exploration of links between financial reporting misconduct and macroeconomic circumstances. Researchers supporting of the relation between macro-factors and financial frauds offer mixed results. Economic boom and bust directly affect the reporting quality of organization (Povel, Singh, & Winton, 2007). Internal monitoring mechanism of firms, principally shaped by external monitoring bodies, i.e., the rule of law, enforcement agencies, shapes financial reporting practices of the firm (Amiram et al., 2018; Sadaf, Oláh, Popp, & Máté, 2018).

2.4 Techniques for Fraud Detection

One of the primary goals of this study includes detecting frauds in publically available data (published financial reports of firms) by applying various fraud detection techniques. Literature on fraud detection techniques is widely stretched, ranging from accounting and auditing techniques e.g., earnings and accrual management, ratio analysis and pattern deduction, qualitative language and text analysis, to more complex techniques encompassing probability theory, by exploring digit-frequency patterns and other sophisticated machine learning techniques and data mining techniques (Amani & Fadlalla, 2017; Amiram, Bozanic, & Rouen, 2013; Archambault & Archambault, 2011; Beneish, 1999b; Bonsall, Leone, Miller, & Rennekamp, 2017; Cao, Chychyla, & Stewart, 2015; Coderre, 2009; Debreceny & Gray, 2010; Fisher, Garnesy, & Hughes, 2016; Ghafoor et al., 2018; Gray & Debreceny, 2014; Hajek & Henriques, 2017; Kamal, 2016; Kanapickiene & Grundiene, 2015; Kassem, 2016a; J. Kim, Kim, & Zhou, 2017; Kirkos, Spathis, & Manolopoulos, 2007; Lang & Stice-Lawrence, 2015; Máté et al., 2017; Mingzi, Oshiro, & Shuto, 2016; Pietronero, Tosatti, Tosatti, & Vespignani, 2001; Purda & Skillicorn, 2015; Sadique, 2016; Shrestha, 2016; Christopher J. Skousen & Twedt, 2009; Christopher J Skousen, Guan, & Wetzel, 2004; Ullmann & Watrin, 2017). A brief overview of essential techniques is presented in the next section.

2.4.1 Benford's Law

The ground-breaking research in the field of data science was carried out by Simon Newcomb, published in (American Journal of Mathematics); Frank Benford in 1938 rediscovered the same phenomenon and put it as a law to what we know as Benford's Law (Benford, 1938). Simon Newcomb found that all the digits do not appear with the same frequency, noticing the first few pages of the logarithmic book to be more torn than the following pages he confirmed the unequal frequency of randomly occurring digits (Newcomb, 1881). However, he was unable to provide any empirical or statistical explanation for this phenomenon, and the findings went unnoticed for almost sixty years (Nigrini, 2012). Frank Benford in 1938, apparently unaware of Newcomb's findings, rediscovered this Law and it became Benford's Law, first digit law or the law of significant digit (Hill, 1995c). Analyzing the same phenomenon (like Newcomb) of Logarithmic book Benford found, the first few pages were overused than the later pages, thus confirming more naturally occurring digits start with 1,2 or 3 than higher digits (Benford, 1938).

2.4.1.1 Benford's Law and Accounting Fraud Detection Application of Benford's Law in accounting and auditing started in the '90s with Carslaw, since then more than 100 studies have been published in this domain (Nigrini, 2005). Using income figures from financial statements of 220 listed firms in New Zealand from 1981 to 1985, he found a much higher frequency of zeros, as the second digit and much lower than expected frequency of 9, as the second digit in income numbers (Carslaw, 1988). Carslaw's findings on the rounding of second digits corroborate the psychological phenomenon where managers, in order to meet income goals, tend to round up figure 9 to the nearest possible digit. The income numbers like $19.98 million would be rounded to $20 million since $20 million proximate the psychological expectation or reference point of expected income number. Thomas observed a similar phenomenon for US COMPUSTAT firms. Though a similar pattern of earning manipulation is founded for US firms but he observed a lesser degree of deviation from expected frequency (Thomas, 1989). The rounding of the second digit was particularly evident for earning per share. For the firms reporting losses, a negative pattern is observed (more nines and fewer zeros).

Mark J. Nigrini made the novel contribution to the application of Benford's law for accounting and auditing fraud detection was made by Nigrini. His Ph.D. dissertation was based on studying Benford's law conformity to income tax data and population census data of three thousand counties of US. Applying the *distortion factor model* and digital analysis using Benford's Law, he analyzed the non-random behavior of tax-payers (Nigrini, 1992). Dividing taxpayers into low-income and higher-income groups, he found that un-planned tax evasion is more evident in low-income groups based on digit frequency pattern (Nigrini, 1996). The findings opened a gateway for the application of Benford's law to detect anomalies and fraud in accounting and auditing research (Hill, 1998). In another study, Nigrini provided support for the use of Digital Analysis in audit analytics to find the digit frequency (Nigrini & Mittermaier, 1997). This study provided support to the validity of Benford's law for the detection of fraud in reported numbers. Consequently, auditors should analyze the (non)conformity of reported numbers in the planning stage of the audit, as the authentic number should follow the Benford frequency. Benford's law is a good starting point for understanding data anomalies and possible financial misstatement. Nigrini conducted a series of studies in order to check data conformity and the possibility of fraud (Drake & Nigrini, 2000). Analyzing audit data through digital analysis and Mean Absolute Deviation test, one can assume that small difference in actual digit frequency and Benford's distribution are acceptable, but a major difference in two series can signal the possibility of data misstatement and fraud (Nigrini, 1999a, 1999b, 2000). Hill provided a mathematical explanation to Benford's law (Hill, 1995a), and also demonstrated how this law works on stock market data, census data and other accounting data. This study supported the hypothesis that fabricated data do not conform to Benford's distribution. Since Benford's distribution is logarithmic, so when people cook the digits or numbers, they do not take into account its logarithmic distribution (Hill, 1996). Benford's law is applicable to a different unit of currencies too (Pietronero et al., 2001). In explaining the digit pattern of Benford and Zipf series, Pietronero et al., (2001) reproduced the result by using data sets in a different currency, hence confirming the multiplicative property of Benford's series. They also simulated mathematical relation of digit law and linguistic law (Zipf's law). In providing a more comprehensive understanding to it, researchers tested this law on a variety of data series to teste conformity and rounding behavior (Das & Zhang, 2003; Nigrini & Miller, 2009a). Analyzing earning per share of COMPUSTAT data, Das & Zhang, (2003) observed a rounding behavior in numbers to the nearest cent for managing earnings and expected threshold. Managers use accruals for rounding earnings in order to meet behavioral expectation of earnings.

The bankruptcy filing of Enron in 2001 was followed by a heightened discussion on the corporate accounting malpractices. Nigrini (2005) analyzed the earning management practices in Enron to predict the changes in earnings figures and reported an upward earning management in revenue numbers in that period. Also, EPS figures were rounded upward to meet psychological expectation since there were more than expected zeros in the second digit (Nigrini, 2005). Another notable contribution to the application of Benford's distribution in accounting was made by Ley (1996). Using Bayesian approach, he analyzed the one-day return series of Dow Jones Industrial Average and Standard and Poor's Index (S&P). He found that in the distributions that follow Benford's distribution, small changes are more likely to occur than the lager one (Ley, 1996). Extending Bayesian approach for detecting manipulation, Geyer and Williamson (2004) proposed an alternative approach to classical distortion factor model (Nigrini, 1996). Providing an extensive simulation to Bayesian approach, they compared both techniques using tax data (Geyer & Williamson, 2004). Diekman and Jann (2010) argued that in order to affirm the validity of the use of Benford's Law in fraud detection, one has to corroborate that the accurate data conform to Benford's distribution whereas the fabricated data follows some other distribution pattern (Diekmann & Jann, 2010). Ullmann and Watrin (2017) provided a new extension to the application in earnings management and fraud detection. In order to analyze the target driven earning management, they relied on the mean of the distribution of the digits. The mean for distribution was lower for the cooked earning digits as compared to the mean of uncooked earning numbers (Ullmann & Watrin, 2017). Testing GDP data from World Bank and Penn World tables for OECD countries Nye and Moul (2007) found partial support for Benford's Law. Their study raised important questions. For the data that does not conform to Benford's distribution, a theoretical and comprehensive explanation must be sought since it does not guarantee unintentional human error (Nye & Moul, 2007).

2.4.1.2 Conditions for Applying Benford's Law

Un-manipulated dataset automatically constitutes Benford's distribution (Miller & Nigrini, 2008). It was not until Hill (1995) who gave a mathematical derivation to significant digit law. His studies provided a new derivation of classical law in the form of *Central Limit Theorem*. The random samples drawn from distribution (randomly selected distributions) will exhibit Benford's distribution pattern (Hill, 1995a). Benford's law is applicable when certain conditions are taken into consideration (Nigrini, 2000). While analyzing accounts for possible fraud investigation; three issues might emerge

- On what accounts, a digital analysis should be applied?
- What kind of further analysis should be done to better reach the conclusion?
- In what circumstances, digital analysis is ineffective?

In trying to answer these questions Durtschi, Hillison, & Pacini, (2004) provided the circumstances where this law is applicable or not. According to their findings, care should be exercised on the reliance of auditors and analyst when evaluating the accounts of the firm since there are frauds that would not be detected with this law (Durtschi et al., 2004). This law is useful when:

- A resultant series is a combination of two series, e.g. account receivable (unit sold*price per unit)
- Transaction-level data is analyzed, e.g. sales, expenses
- Data set should be large i.e., account should not contain too few observations, e.g. full year's data
- Data is based on accounts that generally conform

For the other datasets, this law loses its applicability. This is true especially when datasets is comprised of assigned numbers, or the data sets have maximum or minimum numbers, e.g. invoices, numbers affected by human bias, e.g. ATM withdrawals; dataset having large sets of numbers that are firm specific; dataset based on accounts with maximum and minimum limits and datasets where transactions are not objectively recorded or where no record is found, e.g. thefts, missed record (Durtschi et al., 2004). Additionally, the data should be numeric. This law does not apply to non-numeric data (Nigrini & Miller, 2009b).

2.4.1.3 Properties of Benford's Law

Benford's Law has some unique set of properties;

Scale Invariance: Benford's distribution is invariant of the scale. A general mathematical understanding of Benford's Law was provided by Pinkham (1961), thus revolutionizing its universality and applicability. He demonstrated that the surface area of rivers measured in different physical standard, e.g. meters, hectors would follow Benford's distribution (Pinkham, 1961). It is particularly essential if series measured in a dollar, e.g. is converted into some other series (euros). The new series will show the same pattern as the original (Nigrini & Miller, 2007; Whittaker, 1983; Wójcik, 2014).

Base Invariance: Base invariant property of Benford's Law was proved by Hill (1995). Generalizing this law, he proved this law is valid irrespective of the logarithmic base used (Hill, 1995b).

Invariance to Mathematical Operation: Benford's series remains constant with addition or subtraction (Allaart, 1997; Nigrini, 1992). When a Benford's distribution is subjected to multiplication, division or raising to a power, the resultant series would also be a Benford's series (Boyle, 1994).

2.4.2 Other Data Mining Techniques

The significant areas of accounting where data mining techniques are applicable include assurance and compliance (Cao et al., 2015; Earley, 2015; Gepp, Linnenluecke, O'Neill, & Smith, 2018; Nigrini, 2011) , analyzing financial health of firms (Maccarthy, 2017; Mir, Ausloos, & Cerqueti, 2014), forensic accounting and fraud detection (Debreceny & Gray, 2010; Lin, Chiu, Huang, & Yen, 2015; Ravisankar, Ravi, Rao, & Bose, 2011). Data mining techniques for financial fraud detection are more reliable since they provide more accurate analysis as compared to traditional regression approaches in detecting financial statement fraud (Chen, 2016). There are limited researches in the field of data mining and analysis in accounting (Ravisankar et al., 2011). Data mining is defined as '*A process that employs mathematical, statistical, artificial intelligence and machine learning to identify and extract useful information from large databases for effective decision making*' (Nemati & Barko, 2001).

Data mining techniques have gained enormous importance owing to larger volumes of accounting data and the prevalent complexities in their analysis (Sharma & Panigrahi, 2012). Applying data mining techniques for fraud risk in regular audit process is hard choice since the auditors have to make a few important considerations (Gray & Debreceny, 2014):

a) type of frauds and anipulation (revenue recognition, asset misappropriation etc.),
b) sources of data (Journal entries, emails) and
c) suitable data mining techniques.

Data mining techniques were used to examine all the aspects of the fraud triangle by using appropriate proxies by Lin, Chiu, Huang, & Yen, (2015b). This study employs both expert questionnaires and data mining techniques such as Logistic Regression, Decision Tree (CART) and Artificial Neural Networks (ANNs), in an attempt to get deeper insight into different fraud factors. The findings reported the empirical strength of ANNs and CART models over logistic regression model incorrectly classifying the fraud presence (Lin et al., 2015). ANNs is a widely used technique of data mining in accounting and auditing research. An average of 50% academic researchers in the field of accounting and auditing have relied on this technique (Amani & Fadlalla, 2017). Such dominance of ANNs might be attributed to its applicability in all sort of problem-solving techniques. Comparing 202 Chinese listed firms (101 with reported fraud cases and 101 non-fraud firms), Ravisankar et al., (2011) argued that Probabilistic Neural Network (PNN) outperformed than all other techniques in terms of its accuracy in fraud prediction. A recent study by Jan (2018) used both financial and non-financial variables in an attempt to build a more comprehensive model for fraud detection (Jan, 2018). Findings of this study also suggested the dominance of ANN, for screening at the first stage, and then processed by CART in the second stage, because of the accuracy in 90.83% of the fraud detection cases. An empirical technique to convert unstructured qualitative attributes into quantitative estimation explored by Frankel, Jennings and Lee, (2016).

An extensive expansion to various data mining techniques and their possible limitations are analyzed by Zhou and Kapoor (2011). Considering the economic environment and business sector of firms are also important factors to be taken into account during fraud detection analysis. Criticizing the limitations of DM techniques in fraud detection, they constructed a model named Response Surface Methodology to link the various data mining techniques to financial variables (Zhou & Kapoor, 2011). Additional limitations of data mining techniques in manipulation detection include its cost sensitivity (Ngai, Hu, Wong, Chen, & Sun, 2011). The cost of misclassification of firms (both Type I and Type II errors) is also essential. Nevertheless, the cost of false negative error has more adverse consequences than the cost of false positive error.

A recent study by Amani and Fadlalla (2017) provides a more comprehensive view of data mining techniques in accounting and proposes an organizing framework. Most of the existing literature on data mining is focused on one goal, i.e. *prediction,* thereby ignoring the other two critical goals: description and prescription. There is also vast focus on only one of the three essential tasks of data mining, i.e. *prediction*, disregarding *description* and *prescription* (Amani & Fadlalla, 2017).

Natural Language processing is also essential techniques with widespread applications in fraud detection. Language-based models and language credibility analyses are gaining an important space in accounting fraud research. Using language-based models, Purda and Skillicorn, (2015) used the Management Discussion and Analysis (MD&A) section of the annual reports based on Accounting and Auditing Enforcement Release (AAER) filings of the firms. They could correctly classify 82% of the reports (fraud or non-fraud) using the top 200 most predictive words. Using a cross-country analysis, Lang and Stice-Lawrence, (2015) presented a textual analysis of 15000 non-US firms. According to their findings, textual characteristics and quality of disclosure are higher in the countries with strict accounting standards and stronger oversight. Empirical techniques to convert unstructured qualitative attributes into quantitative estimation was explored by Frankel, Jennings and Lee, (2016). Using word counts from MD&A, quantitative MD&A accruals were estimated with actual accruals for *firm-year* observation. The findings of this study corroborated the use of qualitative attributes with quantitative to better understand the complex fraud process (Frankel et al., 2016).

2.4.3 Accruals and Earning Management

The notion of accruals and earning management (EM) is crucial owing to their effective use in corporate misconduct research. The researchers (both academicians and practitioners) are widely divided on their interpretation of this terms, yet there is broader consensus on the application of earning management in financial misreporting and fraud detection (Dechow & Skinner, 2000). EM is defined in the literature as '*the use of management's judgement in preparing and structuring financial reporting transactions, in such a manner that the* *resultant altered financial reports can therefore either mislead the stakeholder's perception about actual performance of the company, or can affect the other outcomes that rely on these reported earning figures*' (Healy & Wahlen, 1999). This definition leads us to delineate two underlying intents of earning management; a) opportunistic and b) informational.

The former highlights the situation where managers use EM for meeting analysts' forecast (Beneish & Nichols, 2005), industry targets (Wood, 2017), pressure of debt covenants (Parte-Esteban & Ferrer García, 2014) and management compensation (Dechow, Myers, & Shakespeare, 2009; Watrin & Ullmann, 2012). While the *informational* perspective highlights the cases where managers 'cook the cooks' to send a positive signal about their performance (Kedia & Philippon, 2009) and for income smoothing (DeFond & Park, 1997; Godfrey & Jones, 1999). Schipper (1989) defined EM as '*a purposeful intervention in the financial reporting with the goals of obtaining some private goals, instead of merely communicating the neutral results of firm's operation*' (Schipper, 1989).

This study follows the concept of Healy and Wahlen (1999) where EM is an intentional act of deceiving the stakeholders by presenting a false picture of the firm's performance. As a reliable indicator of financial reporting fraud, Nigrini (2005) analyzed the earnings reports released by Enron during 2002 and 2003 and reported the rounding behavior. The result of digit frequency analysis of reported earnings figure and earning per share (EPS) showed an upward management. Hence the presence of more zeros in EPS confirmed the intentional rounding of revenue numbers in Enron (Nigrini, 2005). EM has adverse consequences for the economy. The firms convicted of earning management practices are reported to be too impulsive in terms of their hiring and investment decision, thus distorting business cycle and efficient allocation of resources (Kedia & Philippon, 2009). Once incidences of earning management are caught, this can result in a wave of unemployment and decreased investment.

Earning management and accruals is a reliable indicator of potential fraudulent financial reporting in the firms. The firms subject to enforcement action by SEC show a strong incentive for earning management (Jones, Krishnan, & Melendrez, 2008). The authors, in an attempt to examine the relationship between discretionary accruals and the probability of fraud employed logit model using a sample of fraud firms, and a control sample of non-fraud firms. The results corroborated the ability of accrual quality and earning management as a strong predictor of firms' manipulation practices. The discretion in accounting choices and consequent flexibility offered by GAAP and other standards allows room for financial fraud. Many studies criticized the regulatory bodies and standard setters for their inefficiency in monitoring and regulating corporate disclosure practices (Matsumura & Tucker, 1992; Ravenda, Valencia-Silva, Argiles-Bosch, & Garcia-Blandon, 2018).

Ravenda et al. (2018) used a model of discretionary accruals and earning management to unveil how flexibilities in accounting choices are used to mask the unethical practice of money laundering executed by mafia firms in Italy. The reported results confirmed the implementation of earning management practices in the firms charged of money laundering by the judiciary prior to confiscation year. Earning management in these firms is done to *smooth* the earning figures, before carrying out the illicit transfer of money.

2.4.4 BENEISH M-SCORE

Fraud and manipulation detection and deterrence endured one of the principal emphases for forensic accounting researchers and regulators. As a consequence, numerous models and successful techniques emerged as an outcome of their continuous efforts. Regardless of their continuous efforts to curb financial reporting fraud, a large number of companies are involved in alleged fraudulent practices and have skills to remain *undiscovered* by regulators and enforcement authorities (ACFE, 2014). It is due to the fact that perpetrator might have developed compulsory talents to *conceal* and *convert* his action into some legitimate outcome by camouflaging his action, thus making detection extremely hard for fraud examiners and/or regulators and halt the detection process (Coderre, 2009; Dorminey et al., 2012; Zhou & Kapoor, 2011). Besides, the costs associated with the detection of frauds and the timing-gap between the actual event of fraud and its detection adds to the loss inflicted by frauds on the shareholders and the overall capital markets (ACFE, 2014; Dechow et al., 2011).

A more sophisticated fraud detection model is presented by Messed D. Beneish that allows researchers and analysts to detect frauds prior to the public declaration of fraud events by regulators or other channels (Beneish, 1997, 1999b). This model is prevalent in fraud detection owing to its *simplicity* of techniques and data requirement that is limited to only publically available accounting data (two years). As suggested by the author, this model is a useful predictor of firms’ manipulated financial statements, serve as a preliminary screening device for analysts, investors and regulators. All the required data for this model can be gathered from published financial statements of the companies. Since identifying manipulators and collecting data is one of the major challenges in fraud related research, one of the main reasons for using M-Score is the convenience of data availability. As it requires only two years of data to test this model, the regulators like SECP can inexpensively apply this model to screen the companies for any possible manipulation. The initial model successfully identified approximately half of the firms involved in earning manipulation prior to their public revelation (Beneish, 1999b).

Using a sample of firms that were subject to enforcement actions by SEC enforcement release from 1987 to 1993, Beneish presented a model, called *M-Score* (Manipulator Score) which is a dichotomous (1,0) measure of manipulators/non-manipulators (Beneish, 1999b). The initial model was presented to distinguish between GAAP violators[4] and firms that are involved in aggressive earning management. *M-Score* proved to be a successful predictor of 76% of the reported cases of manipulation by SEC (Ezrien, Md Salleh, & Ahmad, 2016). This model also attempts to generate a timely forecast of the likelihood of manipulation of financial reports by firms and can be implemented as a complementary tool with Altman Z-score for forensic accounting investigations (Maccarthy, 2017). The reliability of this model as an effective manipulation detection tool could be inferred from the fact that it was a successful predictor of fraud for more than 50% of the cases prior to their public disclosure.

Beneish, later with others, presented a complementary model that is named as *the probability of manipulation model* (PROMB) or *Beneish probit model* and correctly identified more than 70% of manipulation (Beneish, Nichols, & Lee, 2011). Using this model Repousis (2016) reported an enhanced tendency of sample firm for financial reporting manipulation. The results of the model evidenced that 33% of firms were involved in the manipulation of financial statements.

Beneish M-Score is a powerful fraud detection tool, in most of the empirical investigations, with an insignificant error rate (Anh & Linh, 2016). Tarjo & Herawati (2015) implemented this tool to investigate earning manipulation in the fraud firms taken from Capital Market Supervisory Agency database and reported substantial execution of this model in correctly identifying more than 77% of fraudulent firms. Ezrien et al. (2016) used a sample of firms where top management was charged for SEC Malaysia for fraudulent financial reporting. Their finding reinforced the efficacy of *M-Score* technique in correctly classifying the manipulator firms (more than 84%), thus advancing it as a robust fraud detection tool. This model is further extended by researchers to enhance its expected effectiveness as a fraud detecting tool. Dechow et al. (2011) extended the initial M-Score model by adding other predictors to financial manipulation. Off-balance sheet, non-financial variables and variables related to the market were found to be a significant determinant of financial reporting fraud,

[4]. Here we defined them as Manipulators or Fraudulent Firms.

which enabled authors to draw *Fraud Score Model*. F-Score, similar to M-Score, is a dichotomous measure of fraudulent firms, thus serve as a *red flag* for fraud.

Table 2.1: Prior Studies on Financial Statement Fraud

Sr. No.	Reference	Country	Purpose/ Objective	Sample	Methodology	Major findings	Classification Accuracy
1	(Persons, 1995)	US	To Identify factors associated with fraudulent financial reporting using financial statement data	103 Fraud firms/103 Non-Fraud Firms	Stepwise Logistic Model	Financial leverage, capital turnover, asset composition and firm size are significant determinant of fraudulent financial reporting.	71.50%
2	(Beasley, 1996)	US	To test whether larger amounts of outside members on a board "significantly reduces the likelihood of financial statement fraud	75 Fraud Firms/75 Non-fraud firms	Logistic Regression	No-fraud firms have boards with significantly higher percentages of outside members than fraud firms.	N/A
3	(Nigrini, 1996)	US	To facilitate whether non-random human behavior could assist in detection of tax evasion	169,662 observations for interest paid/125,462 observations for interest received	Distortion Factor model (Benford's Law)	The digital frequency based analysis shows that low income tax payers practice unplanned evasion on greater extent that high income tax payers.	60%
4	Hansen, McDonald, Messier, & Bell, 1996	US	To model and predict management fraud based on a set of data developed by an international public accounting firm	77 Fraud/305 Non-fraud firms	Generalized qualitative-response model (EGB2)	EGB2 provides the user with considerable flexibility and power. The study offers evidence that EGB2 can provide useful analysis for complex practical applications.	89.30%
5	(Dechow et al., 1996)	US	To investigate the extent to which earning management can be explained by extant hypothesis,: the relation between earning management and corporate governance and the capital market consequences when earning manipulations are made public	92 Fraud/ 92Control Firms	Logistic Regression	The manipulating firms are more likely to have CEO duality; board of directors is dominated by management, more desire to attract external financing at low cost and less likely to have blockholders.	N/A
6	(Green & Choi, 1997)	US	To develop a neural network fraud classification model using endogenous financial data	49 Fraud/46 Non-fraud	Neural Network	NN have great potential for fraud detection considering an aggregate error rate of about 25%	71.70%

7	(Busta & Weinberg, 1998)	N/A	To distinguish between “normal” and “manipulated” financial data using artificial neural network	800 test observations/800 holdout observations	Artificial Neural Network, Benford's Law	The results show that if data have been contaminated (at a 10 per cent level or more) a Benford analytical review procedure will detect this 68 per cent of the time. If the data are not contaminated, the test will indicate that the data are “clean” 67 per cent of the time	67%
8	(Agrawal, Jaffe, & Karpoff, 1999)	US	To investigate whether the public revelation of fraud affects the managerial turnover	103 Fraud firms/103 Non-Fraud Firms	Logistic Regression	Executive and director turnover tend not to be significantly related to the revelation of fraud	N/A
9	(Beneish, 1999b)	US	To present are a profile of a sample of earnings manipulators, their distinguishing characteristics, and a suggested model for detecting manipulation	74 manipulators/ 2,332 Compustat firms	Probit Regression (M-Score Model)	The results suggest a systematic relationship between the probability of manipulation and some financial statement variables: consistent with the usefulness of accounting data in detecting manipulation and assessing the reliability of reported earnings.	89.50%
10	(Rosner, 2003)	US	To determine whether failing firms’ pre-bankruptcy financial statements more likely to exhibit signs of material income increasing earnings manipulation than those of non-failing firms	51 SEC sanctioned/242 non-sanctioned firms	Wilcoxon Rank-sum Test	As (ex post) bankrupt firms that do not (ex ante) appear to be distressed approach bankruptcy, their financial statements reflect significantly greater material income-increasing accrual magnitudes in non-going-concern years than do control firms	N/A
11	(Li, 2004)	US	To introduce an empirical framework that models the interdependence between corporate fraud and the SEC’s monitoring and takes into account the incomplete detection problem	114 fraud firms/1507 non-fraud firms	Simultaneous Logit Model	Study finds that the magnitudes of the effects of stock-based incentives, corporate governance, and external financing needs on the probability of fraud are more than double those documented by models used in previous studies	N/A
12	(Wang, 2004a)	US	To investigate the economic determinants of firms’ propensity to commit securities fraud and the determinants of fraud detection	560 Fraud firms/64077 comparison sample	Bivariate Probit	The results of this study show that some firm characteristics, investment expenditures, and strength of shareholder monitoring can significantly influence a firm’s cost-benefit tradeoff of engaging in fraud	N/A

13	(Skousen et al., 2004)	Japan	To investigate Japanese managers' manipulation of earnings through rounding earnings numbers to achieve key reference points	1871 firm observations	Benford's Law	Study finds that key reference points are not limited to the first digit, the second, third, and even fourth digits are sometimes used as the reference points of the rounding earnings behavior. The incentives of rounding earnings numbers are negatively associated with the distance of pre-rounded earnings to the next reference point	N/A
14	(Bueno De Mesquita & Smith, 2004)	US	To model the likelihood of fraudulent reporting as a function of each corporation's reported performance; ownership oversight; and institutionally induced incentives to govern truthfully	91 alleged firms/ 372 US publically traded firms	Logit Model	Fraud is more often committed to protect shareholder value, not out of altruism, but to protect the jobs of a firm's senior executives. The results highlight features of corporate governance structure and the appropriate balance between compensation and that structure that is most likely to reduce the risk of fraud.	80%
15	(Efendi et al., 2007)	US	To investigate the incentives that led to the rash of restated financial statements at the end of the 1990s market bubble	95 Manipulator/95 Control	Logistic Regression	Misstatements are also more likely for firms that are constrained by an interest-coverage debt covenant, that raise new debt or equity capital, or that have a CEO who serves as board chair	75%
16	(Efendi et al., 2007)	US	To investigate reputational effects of financial fraud for outside directors of firms accused of fraud	216 Fraud/216 Control Firms	Ordinary Logit/ Simultaneous Logit	Findings show that outside directors are more likely to lose other board appointments when the severity of the fraud allegation is high, and when the outside director sits on the audit committee of the interlocked firms.	N/A
17	(Stanley & DeZoort, 2007)	US	To provides initial empirical evidence on the link between financial restatements, audit tenure, and tenure-related proxies for audit firm expertise and independence	191 Fraud/191 Control	Logit Model	Results of the overall tenure effect reveals that the likelihood of restatement is inversely related to the audit firm's industry market share and audit fees for companies with short audit tenures.	N/A

18	(Jones et al., 2008)	US	To examine the relationship between fraudulent earnings and discretionary accruals, accrual estimation errors, and the Beneish 1999 probabilities of earnings manipulation	118 Fraud firms/Compustat firms	Logit Model	Study find that only the accrual estimation errors estimated from cross-sectional models of working capital changes on past, present, and future cash flows and the McNichols 2002 modification of Dechow and Dichev have predictive power for both fraud and non-fraudulent restatements of earnings.	72%
19	(Perols, 2008)	US	To compare the utility of a fairly comprehensive set of classification algorithms and fraud predictors in financial statement fraud prediction	51 Fraud/15934 non-Fraud	Logistic Regression, Classification Algorithms	logistic regression and SVM provide the best performance under what is believed to be the most relevant prior probability and relative cost estimates	N/A
20	(Dechow et al., 2011)	US	To develop a logistic model to determine the probability of manipulations	680 Manipulators/ Compustat firms	Logistic Regression (F-Score)	Results show that over 60 percent of manipulating firms have F-Scores greater than 1.00 and that the selection of an F-Score cut-off is based on the relative costs of Type I versus Type II errors.	67%
21	(Dechow, Hutton, Kim, & Sloan, 2012)	US	To exploits the inherent property of accrual accounting that any accrual-based earnings management in one period must reverse in another period	680 manipulators/ 209,530 Compustat firm-year	Pooled Regression Model	Results indicate that tests incorporating reversals increase test power by around 40% and provide a robust solution for mitigating model misspecification arising from correlated omitted variables.	78%
22	(Amiram et al., 2013)	US	To create a composite financial statement measure to estimate the degree of financial reporting irregularities for a given firm-year	AAER firms from 2001-2011/ Compustat Firms	Benford's Law	Results suggest that the degree of divergence from Benford’s Law can be used as a tool to detect possible financial irregularities	85%

23	(Dalnial, Kamaluddin, Sanusi, & Khairuddin, 2014)	Malaysia	To investigate whether there is any significant difference between the means of financial ratios of fraudulent and non-fraudulent firms, and to identify which financial ratio is significant to fraudulent reporting	75 Fraud Firms/75 Non-fraud firms	Logit Model	Study found that there are significant mean differences between the fraud and non-fraud firms in ratios such as total debt to total equity, account receivables to sales. In addition, Z score which measures the bankruptcy probability is significant to detect fraudulent financial reporting	72.30%
24	(Lin et al., 2015)	Taiwan	To examine all aspects of fraud triangle using the data mining techniques and employ the available and public information to proxy variables to evaluate such attributes as pressure/incentive, opportunity, and attitude/rationalization	129 fraud companies/ 447 Non-fraud companies	Logistic Regression, Decision Trees (CART), and Artificial Neural Networks (ANNs)	The result shows that the correctness of the classification in ANNs is greater than in CART, and the correctness of the classification in CART is greater than that in logistic in both training and testing samples	91.2% (ANNs), 90.4% (CART), 83% logistic Regression
25	(Mingzi et al., 2016)	Japan	To develop a prediction model for identifying accounting fraud by analyzing the accounting information for Japanese firms	241 fraud firm year observations/ 65,199 non-fraud firm-year observations	Logistic regression	Results show that “accrual quality,” “market-related incentives,” “real-activities manipulation,” “conservatism” and “Japanese-specific factors” are generally useful for detecting accounting fraud	75%
26	(Hoberg & Lewis, 2017)	US	To identify systematic abnormal components in MD&A text in the presence of fraud	55,666 firm-year observations as full sample/ 32,553 firm-year observations as holdout Sample	Topic Modelling	Results provide evidence that fraudulent managers discuss fewer details explaining the sources of the firm’s performance, while disclosing more information about positive aspects of firm performance	N/A
27	(Awang & Ismail, 2018)	Malaysia	To examine the influence of attitude, subjective norm and ethical judgement on unethical financial reporting intention	121 participants	Partial Least Square Structural Equation Modelling (PLS-SEM).	The results indicate that attitude, subjective norm and ethical judgement are significant in influencing unethical financial reporting intention, with ethical judgement having the smallest effect on such intention	N/A

28	(Zhang, 2018)	China	To examine the effect of public governance on a firm's incentive to commit fraud	993 fraud firm-year observations/ 10,575 non-fraud firm-year observations	Probit Regression	Results show that, due to enhanced public governance, firms are less likely to commit fraud in the post-campaign period than in the pre-campaign period	N/A
29	(Jan, 2018)	Taiwan	To establish a rigorous and effective model to detect enterprises' financial statements fraud for the sustainable development of enterprises and financial markets	40 fraudulent companies/ 120 regular companies	Multiple data mining techniques	The empirical findings show that the variables screened with ANN and processed by CART (the ANN + CART model) yields the best classification results, with an accuracy of 90.83% in the detection of financial statements fraud	over 75%

Source: Author's own construction

2.5 Hypothesis Development

2.5.1 M-Score

Beneish divided eight indices of M-Score into three broad categories to describe general characteristics of a manipulator. A manipulator is characterized by: a) higher growth, b) declining asset quality, deteriorating profit margins and growing leverage and c) aggressive accounting practices (Beneish, 1999b). Day's sales in receivable index captures year-to-year change in the receivable to sale, thus a higher value indicates that receivables are growing at faster pace with respect to the sales. It is potential indicator of revenue inflation. Other important indicator of aggressive accounting practices is depreciation index, which measures rate of depreciation in t-1 to the rate of depreciation in year t. A DEPI of higher than 1 indicates that the rate of depreciation has decreased or else firm has done an upward shift in assets' useful life (Dikmen & Küçükkocaoğlu, 2010). Finally, accruals indicate the degree to which firm's accounting profits are supported by cash. The accounting profit of manipulators is less supported by cash profit as compared to non-manipulators or control firms (Beneish, Lee, & Nichols, 2012).

As evidenced by Barton and Simko (2002), firms with greater net operating profit has higher tendency to report a higher than actual income. Asset Quality index captures the percentage of soft assets in the balance sheet. A higher Aqu_I is indicator of potential involvement of the firm the cost deferral. Therefore a positive relation is expected between Aqu_I and the probability of manipulation (Beneish, 1999b; Dechow et al., 2011). Growth of the firm, captured by Sales Growth Index (Sgr_I) doesn't necessarily means that growing firms are involved in the manipulation. However, growing firms are viewed by regulators as more prone to manipulation due to the pressure created by market expectation. Brazel et al. (2009) found that high growth firms have greater incentives to maintain their growth as compared to other firms. So a higher probability of manipulation is reported in the firms with higher sale growth (Brazel, Jones, & Zimbelman, 2009; Perols, 2008). Days' sale in receivable index (Dsr_I) captures the ratio of change in receivable to the change in the sale. If there is no any significant change in the firm's credit policy, this ratio is expected to present a linear structure over time. Beneish argued that a large change in the Dsr_I could be a possible indicator of change in firm's credit policy to increase sales for meeting market expectation, but a disproportionate change in the Dsr_I is indicator of the manipulation (Beneish, 1997). Therefore, a positive relation is expected in the relation between large change in the firm's Dsr_I and the probability of the manipulation (Dikmen & Küçükkocaoğlu, 2010).

Dep_I captures the firm's aggressive accounting practices to inflate profit. Distortion in the depreciation rate is the classical issue of accounting choice. As argued by Beneish, an

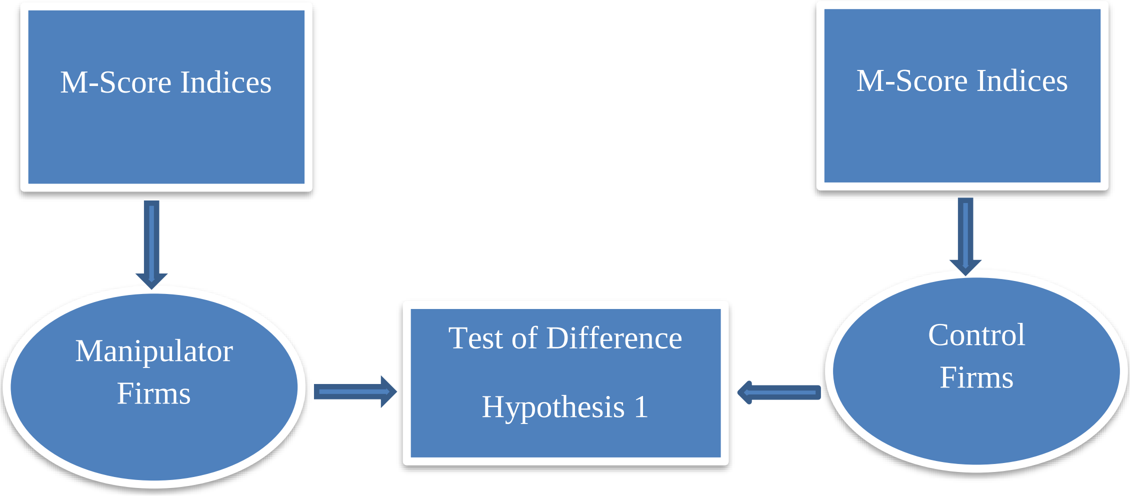

Figure 2-7: Framework for Testing the Difference Hypothesis (H1)

increase in Dep_I (greater than 1) indicates that firm has slowed down its rate of depreciation (Beneish, 1999b). Therefore a positive relation is expected between firm's Dep_I and its probability of manipulation. Sale, general and administrative expenses index (Sgae_I) measures the changes in the ratio of Sgae to sales over time. The correlation between these two measures is expected to remain unchanged if there is not any significant change in the

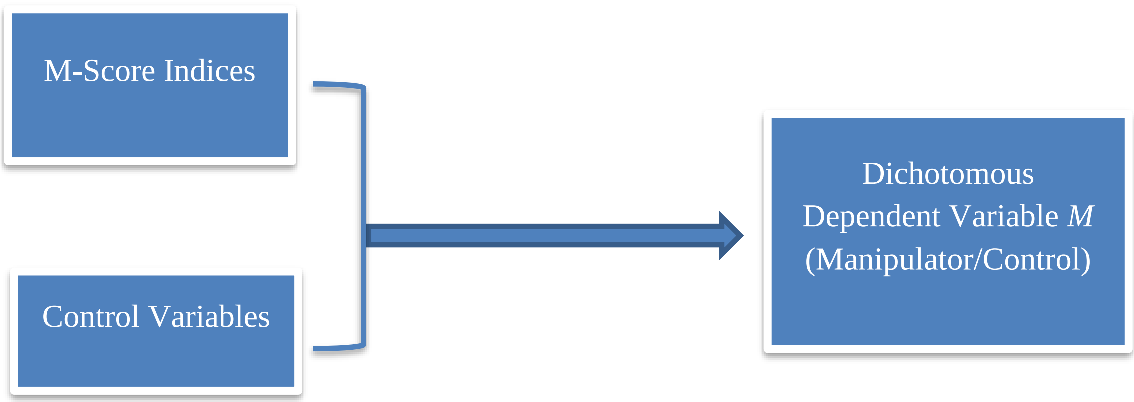

Figure 2-8: Framework for Testing the Hypothesis H2

sale volume. These expenses are variable expenses; they change in proportion to the change in sales volume. A higher Sgae_I means expenses are underpriced and sales are manipulated.

Hence a positive correlation is assumed between Sgae_I and the firm's probability of manipulation (Beneish, 1999b; Dikmen & Küçükkocaoğlu, 2010). Beneish argued that a higher than 1 gross margin index confirms that gross margin has been deteriorated. Decreasing profit margins give firms incentive to manipulate since the poorer profit margins give negative signals about the financial health of the firm. Hence the firms with poorer profit margins are more likely to engage in earning manipulation (Beneish et al., 2012). Wang (2004) reported that the firms with lower profitability and higher growth tend to rely on external market for raising finances (Wang, 2004). Earning manipulation literature also suggests that managers tend to over report the short term profitability prior to any external financing activity (Ronen & Yaari, 2008). Leverage index (Lev_I) captures the incentive for earning manipulation due to debt covenants. A higher leverage index indicates a higher debt in the firm's capital structure. The debt covenant hypothesis also confirms that when firms are on the verge of violating the strict debt covenants, managers are pressurized to manage earnings (Dichev, Graham, Harvey, & Rajgopal, 2012). Hence a higher incentive to manipulate is associated with the firm's higher Lev_I (Perols, 2008). Accruals are also an effective determinant of the firm's manipulation incentive. Higher accrual is also a significant predictor of determination of manipulation. Prior literature on earning manipulation hypothesized that earnings are usually manipulated via accrual component (Sloan, 2001). Therefore misstating firms are expected to have higher accruals than other control firms (Dechow et al., 1996).

Based on above discussion, the following hypotheses (main hypothesis with sub-hypotheses) are drawn.

H1: Manipulators and control firms are different from each other with respect to M-Score variables.

> *H1a: There is no difference between manipulators and control firms with respect to asset quality Index.*
>
> *H1b: There is no difference between manipulators and control firms with respect to sales growth index.*
>
> *H1c: There is no difference between manipulators and control firms with respect to days' sales in receivable index.*
>
> *H1d: There is no difference between manipulators and control firms with respect to depreciation index.*

H1e: There is no difference between manipulators and control firms with respect to selling, general and administrative expenses index.

H1f: There is no difference between manipulators and control firms with respect to gross margin index.

H1g: There is no difference between manipulators and control firms with respect to leverage index.

H1h: There is no difference between manipulators and control firms with respect to total accrual to total assets.

H2: M-Score variables have positive relation with firm's propensity to manipulate (M).

H2a: Asset quality index has positive relation with firm's propensity to manipulate.

H2b: Sales growth index has positive relation with firm's propensity to manipulate.

H2c: Days' sale in receivable index has positive relation with firm's propensity to manipulate.

H2d: Depreciation index has positive relation with firm's propensity to manipulate.

H2e: Selling, general and administrative expenses index has positive relation with firm's propensity to manipulate.

H2f: Gross margin index has positive relation with firm's propensity to manipulate.

H2g: Leverage index has positive relation with firm's propensity to manipulate.

H2h: Total accrual to total assets has positive relation with firm's propensity to manipulate.

2.5.2 Growth and Profitability

Growing firms have higher potential for manipulation due to the fact that they face pressure from the market to meet the performance expectations (Wang, 2004). Hence consideration of growth of the firm is an important factor to highlight manipulation potential and detection risk. Bebchuk and Bar-Gill (2002) predicted that firms with the higher growth potential may exhibit greater propensity of manipulation due to negative performance shock. Hence they manipulate their short term performance to achieve external financing on favorable terms (Bebchuk & Bar-Gill, 2002). Hence firms are able to fund their growth by raising external capital. Elkalla (2017) proposed a positive relation between growth and earning management. Higher growth opportunities may result in political risk due to higher profitability. Hence the firms intend to use income decreasing earning management techniques (Elkalla, 2017). For capturing growth of the firm, this study used firm's sales growth ratio over period of time.

Unexpected performance shocks affect the probability of detection of manipulation (Wang, 2013). If managers manipulate earnings by using income increasing earning management, it would affect the market expectations of the future cash flows. When the resultant cash flows did not meet the expectations, it can raise the suspiciousness among the regulators and analysts, thus raising the chance of detection of manipulation. This study incorporates change in return on assets to measure the effect of performance shocks (Wang, 2004).

Profitability also affects the firm's incentive to commit fraud and carry out manipulation. As discussed earlier, the major motivation for the fraud is deteriorating performance, which gives incentive to the managers to manipulate. Decreasing profit margins tend to send a negative signals about the financial health of the firm (Beneish et al., 2012). However this effect of profitability on the manipulation is ex-ante. We measure profitability by using two different measures. In the first measure, we use gross margin index following M-Score. In the second measure, we incorporate the operating profit margin to measure the impact of profitability on the firm's propensity to manipulate. Hence a negative relation is expected between profitability, the firm's probability of manipulation and the detection of the manipulation.

Based on above empirical literature, we could draw following hypothesis (and sub-hypotheses):

H3a: Sales growth of the firm is positively related to the firm's propensity to manipulate and probability of detection of manipulation.

> *H3a: Sales growth of the firm is positively related to the firm's propensity to manipulate.*
>
> *H3b: Sales growth of the firm is positively related to the firm's probability of detection of manipulation.*

H4: Profitability of the firm is negatively related to the firm's propensity to manipulate and probability of detection of manipulation.

> *H4a: Profitability of the firm is negatively related to the firm's propensity to manipulate.*
>
> *H4b: Profitability of the firm is negatively related to the firm's probability of detection of manipulation.*

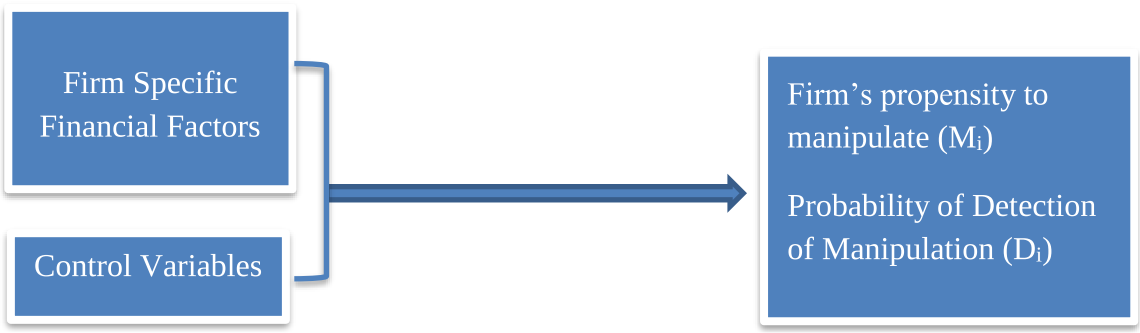

Figure 2-9: Framework for Testing the Relationship between Firm-Specific factors and Dependent Variables D_i and M_i

2.5.3 Investment Intensity

Wang (2004) argues that manipulating firms tend to overinvest. The motivation behind overinvestment includes a) manipulation would lead to a short-term overvaluation of firms, hence reducing the cost of external financing, b) managers may trick analysts and market evaluators by reducing the accuracy of prediction of cash flows, making detection of manipulation a harder task for them. Hence fraudulent firms are expected to have larger investment expenditures as compared to non-fraudulent firms. Moreover, higher investment would make prediction of manipulation a challenging task for regulators and market analysts. Hence this study incorporates ratio of change in fixed assets to total assets to capture the effect of investment intensity (Pindado & Torre, 2006;Wang, 2004). Following Wang (2013), it is hypothesized that investment intensity effects on manipulation and detection of manipulation in a different way.

H5: Investment intensity has a positive effect on the firm’s propensity to manipulate and negative effect on the probability of detection of manipulation.

H5a: Investment intensity has a positive effect on the firm’s propensity to manipulate.

H5b: Investment intensity has a negative effect on the firm’s probability of detection of manipulation.

2.6 Summary of Chapter

This chapter presents a comprehensive literature review of the study. Starting with a brief background, the origin of white-collar crime notion and distinguishing various forms of white-collar crime, and finally the theoretical framework is developed. The theoretical framework encompasses discussion on basic fraud theory, criticism and progress (both theoretical and empirical), thus presenting proposed theoretical framework and its main elements. Since one of the primary goals of this study is to study various firm level factors affecting firm's propensity to commit fraud and manipulation and detecting financial statement fraud, various fraud detection techniques and empirical models are extensively reviewed, including Benford's law, data mining techniques, earning management and finally Beneish M-Score. Seven out of the eight explanatory variables of the M-score model are presented in the form of indices.

3. Material and Methods

3.1 Data and Sample formation

This study is based on firms listed in Pakistan Stock Exchange (PSX). One of the primary goals of data collection is to identify and create a sample of the firms that are subject to enforcement action by Security and Exchange Commission of Pakistan (SECP) due to alleged GAAP violation or any other material violation. Most of the companies have their misreporting practices publically or officially disclosed. Several studies addressed the issue of GAAP violation and enforcement releases issued by regulators, stock exchange and/or security and exchange commission. A notable contribution was made by Dechow, who analyzed 92 AAERs issued by SEC to the two-digit SIC firms for alleged manipulation of material accounting facts and matched them against control sample of same size, industry and stock exchange (Dechow et al., 1996). Similarly, Beneish analyses 64 AAERs covering a period of 1987 to 1993 and matched them against a COMPUSTAT sample of 2,332 US firms for the same year and industry classification as of 64 manipulator firms (Beneish, 1999).

AAERs are considered one of the most reliable sources for data for conducting research on GAAP violation, fraud, earning management and fraudulent financial reporting. These enforcement actions are taken by SEC after a comprehensive analysis of the firms accused of alleged violation of rules of SEC act and other antifraud provisions (Magnanelli, 2010). Nevertheless, the database is a major challenge for the academic researchers exploring fraudulent financial reporting. Even for the US firms, there is lack of consensus in the database of SEC, Audit Analytics (AA) and U.S. Government Accountability Office (GAO) databases for the fraudulent firms (Karpoff et al., 2014). Majority of fraud-related researches are primarily based on a sample of US firms, due to the authenticity of available AAERs. A meta-analysis shows that more than 35% of fraud-related studies are based on US firms (Albashrawi, 2016).

For other countries, studies mostly relied on self-constructed databases on the basis of publically available information from the stock exchange and newspapers. Magnanelli (2010) constructed a database for European firms based on information available on their respective stock exchanges, individual companies' reports, as well as *Loss and Litigation Report* published by GenRe. Correspondingly, Ghafoor et al. (2018) studied enforcement release by Securities Commission Malaysia and Bursa Malaysia to identify fraudulent firms and could analyze a sample of 76 firms involved in fraudulent financial reporting practice. A matching sample of control firms was chosen on the basis of size, industry and year (Ghafoor et al., 2018). Recently, Zhang (2018), using data of enforcement actions taken by Chinese Securities Regulatory Commission (CSRC), analyzed the impact of improved public governance to combat the frauds in recent governmental efforts regarding anti-corruption campaigns (Zhang, 2018). Using data of Japanese firms published by Securities and Exchange Surveillance Commission, Mingzi, Oshiro and Shuto (2016) created and analyzed a database of firms subject to monetary penalties due to their involvement in frauds and suspicious disclosure of financial information.

For the purpose of identifying and creating or own database of firms involved in misstatements, manipulation or any form of financial reporting fraud, this study relies on the data provided by SECP. The names of the firms are not disclosed in any form of analysis since the purpose of this study is to detect, analyze and test the financial parameters of fraudulent firms, by matching them with a sample of control firms. So, revealing the identity of firms is irrelevant to the aim and scope of this study. The list of firms is compiled on the basis of enforcement release available on the SECP website.

SECP is the regulatory body, with one of the most important aims of maintaining the quality of financial disclosure of firms listed in Pakistan Stock Exchange (PSX). Since its incorporation in January 1999, SECP has issued penalties and enforcements against the firms for irregularities and non-compliance behavior (Malik, Liu, & Kyriacou, 2011). At its inception, SECP functioned mostly as a regulator, performing other statutory responsibilities. The functions of SECP were expanded, including the regulation of the corporate sector and overall capital market. The use of SECP enforcement release as a proxy for fraudulent firms has several pros owing to fact that it offers consistency and reliability in the data, thus giving a straightforward and unbiased sample of firms. Besides, SECP investigates only material misstatements and the cases where significant violation had occurred, thus limiting the chances of Type-I error (Dechow et al., 2011). Also, the investigations made by SECP are grounded on strong evidence of manipulation, based on the annual analysis of accounts of firms done by SECP or based on whistle-blowers' information (Hajek & Henriques, 2017). The chances of researcher's individual biases and errors, caused by relying on other classification schemes, are significantly reduced (Mingzi et al., 2016).

As stated earlier, the objective is to identify a sample of firms that are alleged of frauds and manipulation, we started by creating a sample of firms that are involved in material misstatements and other violations, purposefully to deceit the investors and other stakeholders. In order to achieve that goal, the first focus is to collect and make a comprehensive study of the series of the issued enforcements from SECP website. In most of the cases, the enforcement releases were issued against the firms, auditors, and other parties. An in-depth understanding of individual notice and information was mandatory since most of the issued notices were addressing the particular section of company ordinance 1984, that the particular firm is violating. Every single notice and issue was translated, compared and analyzed meticulously to construct an accurate sample of the fraudulent firm.

3.2. Sample Selection

We began by collecting all the enforcements issued by SECP, starting from 2002 to 2016. Next process involves filtering of these enforcement releases to identify the firms that are alleged of accounting manipulation and fraud, in at least one of the issued release. All the other cases that were ambiguous or redundant to reach the conclusion were dropped for the sake of clarity of understanding. Enforcements issued to the firms for other violations of SECP regulations, unrelated to financial statement frauds, were also dropped since the scope of this study covers only financial manipulation and accounting frauds. Furthermore, private firms, firms with incomplete data and financial institutions were also excluded from the sample (Perols, 2008). The sample of firms drawn from SECP is shown in *Table 3.1*. Enforcements for listing violations, failure to comply with regulations, e.g., of timely conduct of annual general meetings (AGM), failure to update annual reports on the website, improper functioning of website were excluded from the list. So in the final sample, we were left with 42 enforcements, particularly addressing the firms for manipulation and financial frauds. Since the population of this study includes all the firms that have been issued enforcements by SECP, the sample size is quite reasonable since this study is addressing only those firms who are accused of accounting and financial manipulation in their financial reports.

Persons analyzed 111 US fraud firms matched against a sample of 111 non-fraud firms using logistic regression technique (Persons, 2005). A fraudulent sample of 38 Greek firms, publically identified as fraudulent, was studied by Kirkos, Spathis and Manolopoulos (2007). Using data mining techniques, the researchers matched these fraudulent firms with an equal sample of control firms. Correspondingly, Debreceny and Gray used journal entries of 29 fraudulent firms using Benford’s Law as a data mining tool and presented digit patterns of the studied firms to analyze the chance of manipulation (Debreceny & Gray, 2010).

Table 3.1: Description of Sample of Manipulator/ Fraudulent Firms Based on SECP Enforcement Release

Total number of enforcement released by SECP during 2002-2016		125
Less: Financial Institutions	7	
Private and Foreign Firms	5	
Firms committing other offenses and non-compliance	66	
Enforcements with unclear information	5	
Total number of firms classified as manipulator/fraudulent		42

Source: author's compilation (2019)

3.3. Selection of Control Firms

Sample of control firms is chosen for matching them against the sample of fraudulent or manipulator firms identified from a thorough analysis of SECP enforcement release. The selection of control firms is to be done cautiously to ensure the comparability of results of the chosen models for identification and analysis of financial frauds. The population for control firms includes all PSX listed firms, excluding those who have been grouped as *fraudulent firms* as well as financial institutions and foreign firms. Various techniques have been used by researchers to identify a set of control firms. Beneish, e.g., used two sets of control firms. One group of control firms were selected based on industry classification, year and size of the firms matched against the fraudulent firms. The other set is chosen based on industry, year and age of the firms matched against firms that have been issued enforcements (treatment firms) (Beneish, 1999). The following essential criteria were kept in mind in the selection of a control sample:

a) *Industry*: Non-fraudulent firms and control firms should be based on the same 2-digit SIC industry classification as fraudulent firms. This is to ensure the credibility of analysis and comparison of the results. The firms identified as fraudulent (or have been issued any enforcement), are excluded from the control sample since control firms represent a sample of 'other than fraudulent firms (Beasley, 1996).
b) *Size*: The size of control firm is matched against the size of the sample of fraudulent firms identified through SECP. Various proxies have been used in the literature for measuring the size of the firm. Following Beasley, control firms are selected based on

the same industry and size as of fraudulent firms. Total assets of the firms are used as a proxy for size (Beasley, 1996).

c) *Age*: Firm age is a crucial deciding factor since the new firms face stricter monitoring from regulators. Beneish stated that age is a deciding element for SEC to begin its investigation for non-compliance behavior. Consequently, younger firms face tighter investigation, leading to an enhanced probability of detection of fraud or misstatement in their financial reporting (Beneish, 1999; Perols, 2008).

3.4. Data Collection

Data collection process starts with the identification of fraudulent firms, based on data from SECP enforcement release. Every single enforcement release is read carefully to decode the type of offense firm has committed, thus reaching a handful of firms that violated GAAP and other accounting regulations. The *manipulation year* (t) is defined in this study as the year; SECP has issued enforcement against the firms for violation (Chu et al., 2018). In order to facilitate (Beneish M-Score) the analysis, data was collected for two years before the fraud year (t-2) and minimum one year after the fraud year (t+1). Therefore, a thorough examination of each document was inevitable to identify firm and year as well. After identifying firms and deciding on criteria for the control sample, the next important step is to collect the data of financial statements for both fraudulent and control firms. For the Pakistani firm, the most authentic source of data is Financial Statement Analysis (FSA) of companies (non-financial) listed at KSE; published by State Bank of Pakistan (FSA, 2015).

FSA is based on two-digit Standard Industrial Classification (SIC) of all the firms listed in PSX. It covers data of all the financial statements and provides additional analysis of important ratios and performance indicators. For most of the fraudulent sample, FSA database was enough to serve the purpose. For other firms, individual company reports were hand collected by considering individual company-year data from their respective websites. For the final analysis, we relied on 221 firm-year observations for manipulator or fraudulent firms; matched against a control sample of 305 firm-year observations.

Table 3.2 shows the two-digit SIC classification of a sample of manipulator firms. Textile and allied sector is the largest group in the overall economy of Pakistan (Iqbal, Ahsan, & Zhang, 2016). Based on the highest total number of listed firms in this sector, 50% of manipulator firms belong to this industry, thus making the largest group of the manipulator in the sample used. The remaining of the sample comprises of Food, Fuel and Energy, Information and Communication, Paper, Chemical and Allied and miscellaneous Manufacturing and Services firms; together making remaining 50% of the sample.

Table 3.2: Industry-Classification of Firms

Panel A: Two-Digit Industry-Classification of Sample of Manipulator Firms Subject to Enforcement

Name of Industry	**SIC**	**Number of Firms**	**Percentage**
Textile and Allied	22,23,31,56	21	0.5
Food	20,54	4	0.095
Fuel and Energy	49	1	0.023
Information, Communication & Transport (Including Transport Equipment)	37,40,47,48	5	0.120
Paper and Allied	26,27	1	0.023
Electrical Machinery & Apparatus	35,36,38	2	0.047
Misc. Manufacturing	39	1	0.023
Chemical and Allied	28	2	0.047
Cement	32	2	0.047
Other Services	89	2	0.047
Coke & Refined Petroleum Products	29	1	0.023
Total Number of Firms Identified as Manipulator		42	100

Panel B: Two-Digit Industry-Classification of Manipulator-Control Firms

Industry	SIC	Number of firms	Percent
Textile and Allied	22,23,31,56	38	0.506
Food	20,54	8	0.106
Fuel and Energy	49	1	0.0133

Information, Communication & Transport (Including Transport Equipment)	37,40,47,48	7	0.093
Paper and Allied	26,27	2	0.0267
Electrical Machinery & Apparatus	35,36,38	3	0.04
Misc. Manufacturing	39	5	0.067
Chemical and Allied	28	4	0.054
Cement	32	4	0.054
Other Services	89	2	0.0267
Coke & Refined Petroleum Products	29	1	0.0133
Total Control Firms	75		100

Source: author's compilation (2019)

3.5. Issues in Data and their solutions

There were two critical concerns of the data that this study has to confront while doing estimation and analysis. Since most of the independent variables are in the forms of indices, incorporating year to year change in the values of financial parameters involves, thus creating the issue of extreme values or outliers. All the variables were, therefore, *winsorized* at 1% and 99% percentile to remove the extreme values. The other potential issue was the case of missing values. In order to overcome the issue of missing data in the variables, we used the technique of *multiple imputation* of data (Brazel et al., 2009). Imputation technique allows us to replace missing data with the set of reasonable values. It is based on the assumption that missing data follows a random pattern (Yuan, 2007). The next process involves analysis of imputed data using binary logistic regression technique.

3.6. Beneish M-Score and Variables

Beneish M-Score is a model, used for detection of manipulation, which triggers the red flags or the essential determinants of financial reporting fraud. The model initially presented by Messod Daniel Beneish (Beneish, 1997), using sets of financial ratios of a sample of manipulators firms and control firms. The general M-score model can be estimated by following equation:

$$M_i = \beta' X_i + \mathcal{E}_i \tag{3-1}$$

Where *M* represents a categorical variable, expressing one as manipulator or fraud, whereas zero represents non-manipulator/non-fraud firm, *X* represents the matrix of determinants of fraud or explanatory variables and ε represents error term.

M-Score, calculated from variables taken from firms' financial statements, thus making the process of fraud detection relatively convenient for the analyst and researchers, expresses the extent to which a firm is a manipulator (non-manipulator). Seven out of the eight explanatory variables of the M-Score model are presented in the form of indices. The argument behind presenting the explanatory variables in the form of indices, as suggested by Beneish, was to eradicate the distortion caused by earning manipulation (Beneish, 1999). These indices are measured by using the data from the manipulation year and the year prior to the manipulation.

3.6.1. Calculation of M-Score

M-Score model is a classification tool; distinguishing manipulators form non-manipulators. Initially, this model was designed to compare GAAP violators (companies subject to enforcement by SEC) and *aggressive-accruers*, in an attempt to understand the variation between detected and undetected earning management (Bonner et al., 2011). M-Score is calculated by using the following expression,

$$\begin{aligned}\text{M-Score } = &-4.84 + 0.92 \times DSR\_I + 0.528 \times GRM\_I + 0.404 \times AQU\_I + 0.892 \times SGR\_I + \\ &0.115 \times DEP\_I - 0.172 \times SGAE\_I + 4.679 \times TATA - 0.327 LEV\_I\end{aligned} \tag{3-2}$$

where DSR_I represents days' sales in receivables index, GRM_I represents gross margin index, AQU_I as asset quality index, SGR_I shows sales growth index, DEP_I shows depreciation index, SGAE_I represents selling, general and administrative expenses index and TATA represents total accrual to total assets. As a rule of thumb, Beneish calculated a cut-off M-Score of -2.22. The M-score value greater than -2.22 shows a higher probability that a firm is involved in manipulation or fraud. The M-Score calculation is reliable for flagging the frauds and embezzlement since any such activity leads to imbalance the equation thus leading to a higher M-Score value than the cut-off value. Thus M-Score is a reliable source for financial fraud examiners (Mantone, 2013).

M-Score is a probability model; it may not capture 100% of manipulation (Maccarthy, 2017). Nevertheless, Beneish could use this model to correctly identify 76% of manipulators (Type-I error is 24%) and falsely identify 17.5% of non-manipulators (Type- II error) (Beneish, 1999).

3.7. Variables Analyzed

In this section, we will discuss briefly the rationale behind the variables chosen for manipulation detection, including indices used for M-Score calculation categorized here as independent variables, and dependent and control variables, respectively. A detailed explanation of variables, including their proxies, source and resource is, discussed in Table *3.3*.

3.7.1. Dependent Variable

The dependent variable of this study is 'manipulator', representing firms identified as fraudulent based on SECP enforcement data. The manipulator is an indicator variable, where 1 represents manipulator or fraudulent firms, and zero represents non-manipulator or control firms. SECP is the most authentic source of data of corporate financial shenanigans since the enforcement against the firms are issued after a detailed analysis of financial statement and information from other formal/non-formal channels (Dechow et al., 2011). Attributing Beneish (Beneish et al., 2012) who used Probit regression model of comparing the manipulator firms against a sample of control firms, this study is based on analyzing the sample of manipulators against a matched sample of non-manipulators or control firms listed in PSX.

3.7.2. M-Score Variables

3.7.2.1.Asset Quality Index

Asset quality is a measure of a non-current asset other than property, plant and equipment to total assets for a given year. The index of asset quality (*AQU_I*) is measured by dividing asset quality measures at time *t* to the asset quality measured at time *t-1*. *AQU_I* suggests the firm's inclination toward cost deferral and therefore, an increased assets' realization risk. Beneish expected a positive relation between AQU_I and earning manipulation (Beneish, 1999b). A higher AQU_I is also an indicator of fraud in the form of asset overstatement (Sadique, 2016; Siegel, 1991).

3.7.2.2.Sales Growth Index

Sales growth index (*SGR_I*) is measured by dividing sales at time *t* to the sales of prior year *t-1*. For the firms committing revenue overstatement, SGR_I generally increases (Abbasi, Albrecht, Vance, & Hansen, 2012). Growth in sales does not necessarily means that the firms are indulging in manipulation activities, but growing companies are viewed by professional as firms having the high inclination to manipulation owing to their position in the industry and need for more capital thus exert pressure on its management to manipulate(ACFE, 2016). The incentive to manipulate is also more prevalent for the growth companies as compared to firms with less growth especially where growth firms are facing a crisis in the share prices. The situation leaves growth firms in the pressure to manipulate in order to meet analyst forecast, investors' and market expectation (Skinner and Sloan, 2000). Beneish, therefore, proposed a positive relationship between the growth of sales and earnings manipulation incentive (Beneish, 1999b).

3.7.2.3.Days' Sales in Receivables Index

Days' sales in receivable *(DSR)* is the ratio of days' sales in receivable at time *t* to the days' sales in the prior year (*t-1)*. The index of DSR is calculated by dividing the ratio of DSR at *t* (here we denote *(t)* as the year when firms have manipulated earnings) to DSR calculated by using figures of sales and receivables of prior year (*t-1)*. The resultant index is represented as days' sales in receivables index (*DSR_I)* (Beneish, 1999a). This index captures the pattern of receivables and sales in the year of manipulation concerning prior year values. Revenue is the most important variable subject to manipulation. Therefore a higher value of DSR_I might emerge due to alteration in firms' credit policy, thus resulting in revenue and consequent earning manipulation (Abbasi et al., 2012; Green & Choi, 1997).

3.7.2.4.Depreciation Index

Depreciation index (*DEP_I*) can be calculated by dividing the rate of depreciation at time (*t-1)* to the rate of depreciation at time *(t).* Whereas, the depreciation rate for any time period, can be calculated by dividing depreciation to the sum of depreciation and property, plant and equipment (Beneish, 1999a). A *DEP_I* greater than 1 is the indication of reduced depreciation rate of the firm that can signal the likelihood of income increasing method being adopted by the company by altering the assets' useful life. Therefore, an increased DEP_I can signal the firm has decelerated the depreciation of its assets and is probably a red flag for earning manipulation (Beneish, Lee, & Nichols, 2012).

3.7.2.5.Selling, General and Administrative Index

Selling, general and administrative index *SGAE_I* is calculated by dividing selling, journal and administrative expense to sale at time *(t)* to the subsequent prior year *(t-1)* selling, the general and administrative expense to the sale value. An increasing *SGAE_I* is a signal that firm might be engaging in earning manipulation practice. According to Beneish, when firms artificially accelerate their sales, *SGAE* deteriorates, thus representing a small proportion of firms' sale, thus depicting a higher probability of manipulation and fraud (Abbasi et al., 2012; Beneish, 1999b).

3.7.2.6.Gross Margin Index

Gross margin index (*GRM_I*) is the ratio of gross margin calculated at the year prior to manipulation *(t-1)* to gross margin calculated at manipulation year *(t).* A decreasing gross margin or GRM_I greater than 1 is an indicator of worsening performance of company overtime. A higher than 1 GRM_I is very rare to occur especially when the firm is engaged in revenue manipulation. However, a decreasing gross margin also signals negative aspect of the company's performance. Beneish proposed a positive relationship between firms' declining performance, higher GRM_I, and its propensity to manipulation (Beneish, 1999).

3.7.2.7.Leverage Index

Leverage index (*LEV_I*) is a ratio of leverage (debt/total asset) at time *t* to the leverage ratio calculated at prior-year *(t-1).* A greater *LEV_I* indicates an increase in leverage in the manipulation year as compared to subsequent prior-year value. The increasing debt to asset ratio shows the poor performance or economic deterioration in the firms that presenting more incentives for the firm's managers to manipulate (Beneish et al., 2012). A higher *LEV_I* also points out to the probability that managers are factiously raising assets without any increase in debt in the capital structure. *LEV_I* also captures the incentive for debt covenants, and external pressure the managers are exposed to, thus leading them to manipulate (Skousen, Christopher J., Smith & Wright, 2015). LEV_I is also a predictor of financial distress and represents external financing needs, therefore it can predict a firm's propensity to commit fraudulent act and misstate (Wang, 2004).

3.7.2.8.Total Accruals to Total Assets

Total accrual to total assets (TATA) is the only variable presented by Beneish that is not in the index form. Total accruals are calculated by subtracting depreciation from the change in working capital other than cash. *TATA* is the ratio of total accruals at time *(t)* to the total asset at time *(t).* Accruals are an important indicator or red flag for accounting manipulation by management discretion since it highlights the variation in accounting profit and cash. Therefore as presented by Beneish, a higher positive value of accruals can signal earning manipulation (Beneish, 1999). Accruals proxy has been widely used in empirical studies on financial misconduct research (Frankel et al., 2016; Karpoff et al., 2017; Kothari et al., 2005).

3.7.3. Other Variables

3.7.3.1 Inventory Overstatement

Inventory overstatement is one of the significant red flags in the cases of manipulation of earning and other reported numbers (Persons, 2005). Researchers confirmed that inventory overstatement represents a vast majority of AAERs issued by US SEC to manipulating firms, counting roughly three fourth of issued enforcements (Feroz, Park, & Pastena, 1991). Improper valuation of inventory and recording bogus inventory was observed in many firms charged of manipulation (Loebbecke, Eining, & Willingham, 1989). Moreover, it can also affect the relation of sales and cost of goods sold and hence reported income.

3.7.3.2 Operating Income to Sale

Operating Income to sale is the ratio of profit before interest and taxes to the net sale. Fraud related research confirmed that firms' propensity to manipulate is accelerated by poor performance. A worse than expected performance provides more significant incentives to the firm's management for manipulation and fraud (Persons, 2005). Profitability ratios are considered vital to the detection of corporate misconduct since they decipher investment, financing and liquidity position of firms. A declining profit margin motivates the firm to overstate its revenue and/or understate its expense (Church et al., 2011).

3.7.3.3 Investment Intensity

Investment decisions (INV) of the firm are also an important indicator of litigation risk as managers may attempt to mask the detection of fraud by making a new investment (Qiu, 2009). Corporate misconduct literature suggests that most firm tend to overinvest due to

a) reduction in the cost of financing due to fake overvaluation of firm and

b) extensive investment can pose difficulty for the analysts and investors to correctly predict the firm's cash flow (Noor, Sanusia, Heang, Iskandar, & Isa, 2015).

Hence investment affects the probability of detection of manipulation and fraud. Wang (2004) argued that fraudulent firms have higher investment expenditure as compared to the non-fraudulent firm. The proxy used in this study for capturing INV is the ratio of *change in net fixed assets at time (t) to book value of the total asset at time (t)* (Pindado & Torre, 2006).

3.7.3.4 Unexpected Performance Shock

Performance and especially poor performance can trigger investors and analysts; it might followed by investigation by regulators. Financial performance is an essential indicator for measuring potential fraud detection and deterrence since manager might misstate the performance to mask the flagging firm performance. Bad performance of the firm or unexpected performance shock is an indicator of commencement of manipulation as argued by Chen, Firth, Gao, & Rui (2006) and Wang (2004). In order to capture unexpected performance shock, this study will employ a change in ROA (ratio of net income to the book value of total assets).

3.7.3.5 Growth

The second measure we used to capture the firm's performance is *growth*. Growth is the ratio of *sales revenue at time (t) to the sale revenue at time (t-1)*. For the purpose of clarity, this study excludes accrual-based sale, i.e., credit sale following (Dechow et al., 2011). High growth firms are more likely to indulge in fraud. Another rationale behind firm's growth and detection of manipulation, as suggested by corporate misconduct literature, is the fact that high growth firms are subject to higher scrutiny by enforcement agencies and regulators than their low growth industry peers (Dechow et al., 2011).

3.7.3.6 Working Capital Accruals

Previous researches supported that working capital accrual is an essential predictor of fraudulent financial reporting since it can capture overstatement of earnings. Working capital accruals incorporates net operating assets; thus having a direct link to revenue recognition and finally gross profit of firm (Dechow & Dichev, 2002). An earning is deemed as fraudulent when there is no corresponding cash flows associated with it (Brazel et al., 2009).

3.7.3.7 Change in Inventory to Change in Sale

Inventory growth to sale growth ratio is also used in litigation literature for the potential red flag of manipulation. It is the difference between inventory and sale. A higher subjectivity and managerial judgement is involved in the valuation of inventory, hence it is prone to manipulation (Kirkos et al., 2007). A positive inventory to sale ratio (inventory is growing faster than sales) signals the presence of potential fraud following Rosner (2003) and Sadique (2016).

3.7.4. Control Variables

In this section, we will discuss various other control variables that might affect the firm's incentive to manipulate and commit fraud.

3.7.4.1 Size

Firm's ability and incentives to manipulate is also related to its size, thus using this variable as control can bound the probability that size is affecting the results. Total assets are used as a proxy for the firm's size (Brazel et al., 2009). Correspondingly, Dechow et al. (2011) argued that firms having higher market capitalization are more likely to be fraudulent. More than 13% of manipulator firms were from top docile in term of market capitalization. The probability of being caught by regulators is also higher since larger firms face more monitoring and review from regulators (Dechow et al., 2011).

3.7.4.2 Age

Age of the firm is defined as the *number of years since it has been listed in PSX* (Brazel et al., 2009). Age of the firm is a crucial factor in conducting fraud-related research as younger firms face strict scrutiny from regulators. The probability of younger firms being caught by SECP for any misconduct is thus relatively higher. Another probable explanation for this can be the fact that younger firms are in the position of higher financial distress (Beneish, 1997).

Table 3.3: Variables, Sources, Resources and Proxies Used

Variable Names	Acronyms	Measurement Proxy/Operationalization	Data Sources	Resources
Manipulator	*M*	Indicator variable, 1 for manipulator and 0 for non-manipulator	SECP	(Beneish, 1999)
Factors Affecting Firm's Propensity to Commit Fraud				
Asset Quality Index	*AQU_I*	(1-Current Assets_t+ Property, Plant & Equipment_t (PPE) /Total Assets_t) / (1-Current Assets_{t-1}+Property, Plant & Eqipment_{t-1}/Total Assets_{t-1})	(FSA)	(Beneish, 1999)
Sales Growth Index	*SGR_I*	Total Sales_t/Total Sales_{t-1}	(FSA)	(Beneish, 1999)

Days' Sales in Receivables Index	*DSR_I*	(Receivables$_t$/Sales$_t$) / (Receivables$_{t-1}$/Sales $_{t-1}$)	Financial Statement Analysis (FSA)	(Beneish, 1999; Repousis, 2016)
Depreciation Index	*DEP_I*	(Depreciation$_{t-1}$/Depreciation$_{t-1}$ +PPE$_{t-1}$) /(Depreciation$_t$ / Depreciation$_t$+ PPE$_{t)}$	(FSA)	(Beneish, 1999)
Selling, General And Administrative Index	*SGAE_I*	(Selling, general & administrative Expenses$_t$/Sales$_t$)/(Selling, General and administrative Expenses$_{t-1}$/Sales$_{t-1}$)	(FSA)	(Beneish, 1999)
Gross Margin Index	*GRM_I*	Gross Margin$_{t-1}$ /Gross Margin$_t$ =(Sales$_{t-1}$-Cost of Goods Sold$_{t-1}$/Sales$_{t-1}$) / (Sales$_t$-Cost of Goods Sold$_t$/Sales$_t$)	(FSA)	(Beneish, 1999)
Leverage Index	*LEV_I*	(Long-Term Debt$_t$ + Current Liability$_t$/Total Assets$_t$) /(Long-term Debt$_{t-1}$+Current Liability$_{t-1}$/total Assets$_{t-1)}$	(FSA)	(Beneish, 1999)
Total Accruals To Total Assets	*TATA*	Net Income$_t$-Cash Flow from Operations$_t$/Total Assets$_t$	(FSA)	(Beneish, 1999)
Other Variables				
Inventory Overstatement	*Inven_ovsst*	Inventory$_t$-Inventory$_{t-1}$/Total Assets$_{t-1}$	(FSA)	(Rosner, 2003)
Operating Income to Sale	*OI/Sale*	Net Profit$_t$/Cash Sales$_t$	FSA	(Persons, 2005)
Factors Affecting Detection of Manipulation				
Investment Intensity	*INV*	Net Fixed Assets$_t$-Net Fixed Assets$_{t-1}$+DEP$_t$/Total Assets$_t$	FSA	(Wang, 2013)
Unexpected Performance Shock	*CROA*	Return on Assets$_t$-Return on Assets$_{t-1}$/Return on Assets$_{t-1}$	FSA	(Chen et al., 2006; Wang, 2004)

Growth	*GROWTH*	Sale Revenue$_t$-Sale Revenue$_{t-1}$/ Sale Revenue$_{t-1}$	FSA	(Dechow et al., 2011)
Working Capital Accruals	*WC_Accr*	(ΔReceivable$_t$+ΔInventoryt+Δ Other Current Asset$_t$-ΔAccount Payable$_t$-Change in current Portion of Long-term Debt$_t$-ΔTax Payable$_t$)/Total Assets$_{t-1}$	(FSA)	(Dechow & Dichev, 2002)
Change in Inventory to Change in Sale	*Inven/Sale*	Change in inventory/ Change in Sale	FSA	(Rosner, 2003)
Control Variables				
Size	*SIZ*	Natural log of Total Asset$_t$	(FSA)	(Brazel et al., 2009)
Age	*AGE*	The number of years elapsed since the firm is listed at PSX.	Annual Reports	(Qiu, 2009)

Source: author's compilation

3.8. Empirical Methodology

Firm's choice of engaging in fraudulent financial reporting and manipulation practices depends upon how the firm would see the expected benefits and cost associated with the commission of such act. The cost of committing a fraudulent act, to mislead investor, can be broken down into

a) probability of detection of fraud and
b) ex-post regulatory penalties imposed on firms for fraud (Wang, 2004).

The focus of this study is to analyze the fraud detection methods to assess their usefulness and investigate the firm-specific attributes distinguishing fraudulent firms from the sample of non-manipulators or control firms.

As discussed earlier, this study complements the Beneish Model for identifying manipulator. We also introduce a few modifications in the initial M-Score Model. Most of the previous researches on fraud and corporate misconduct have applied probit/logit regressions since these models are the typical forms of qualitative response models, they can predict the probability that an element with certain attributes will belong to a particular class (Hansen, McDonald, Messier, & Bell, 1998). Probit/logit models were typically used in the estimation of most of the empirical researches on fraud detection where a dichotomous dummy in the form of 1 for *manipulator* firms and zero for non-manipulators have been used. (e.g., Beasley, 1996; Beneish et al., 2011; Chen, Yaşar, & Rejesus, 2008; e.g., Dechow, Ge, Larson, & Sloan, 2007; Kedia & Philippon, 2009; Skousen, Kevin & Smith, 2015). The following expression can estimate a typical single equation model:

$$Prob(M) = Prob(Z = 1) = \beta X + \varepsilon 1 \tag{3-3}$$

where Z is a dichotomous variable, equals 1 when *Prob(M)>0* and zero when *Prob(M) ≤ 0*. *X* represents the vector of the characteristics or determinants of the manipulator. Equation (3-3) looks like a conventional probit function with a dummy as a dependent variable. However, the variable Z is not directly measurable; there is a conditional probability associated with it. A manipulator in the above equation is only observable if it is detected. Contrary to this, many fraud cases go undetected. A zero value of Z may show that the firm is non-manipulator or otherwise undetected manipulator who can conceal its act from regulators (Yost, 2015). A simple probit model assuming perfect detection will hence create biased estimates. In order to overcome this issue of partial observability of fraud and manipulation, we use a bivariate probit model of Feinstein (1990).

3.8.1 Estimation Technique

As discussed earlier, we can observe only those frauds that have already been detected. A fraud event we observe is therefore, a combination of manipulation event and detection of that manipulation. In order to address this issue of identification, we assume a system of equation, separating *manipulation (M)* and *detection of manipulation P(D)*, following the model of Poirier (1980) and Feinstein (1990).

A firm (i), has potential of manipulation denoted by $M_{i,}$ (a binary variable equals to 1 if a firm commits fraud and zero otherwise), let D_i a binary variable showing a firm i potential to commit fraud equals 1 if the firm has been detected as manipulator by regulators and zero otherwise; let Z_i is a dichotomous variable equals one of the firms (i) gets caught by regulators after committing fraud and zero otherwise. It can be represented in the following equations:

$$M_i = \mathrm{X}_{M,i}\boldsymbol{\beta}_M + \boldsymbol{\varepsilon}_{M,i} \tag{3-4}$$

$$D_i = \mathrm{X}_{D,i}\boldsymbol{\beta}_D + \boldsymbol{\varepsilon}_{D,i} \tag{3-5}$$

Where $X_{M,i}$ represents the factors of firms (i) or determinants of manipulation and $X_{D,i}$ represents the characteristics of firm i that helps regulator in the detection**.** M=1 represents a manipulator (*$M_i<0$*) and $M_i=0$ shows otherwise. Similarly, $D_i=1$ when a firm is detected as a manipulator ($D_i>0$) and $D_i=0$ otherwise. M_i and *D_i* are not directly observable; it can be observed in the form of probability Z_i as,

$$Z_i = M_i D_i \tag{3-6}$$

$$\begin{aligned} Prob(Z_i = 1) &= Prob(M_i = 1, D_i = 1) \\ &= Prob(M_i = 1)\ Prob(D_i = 1|M_i = 1) \end{aligned} \tag{3-7}$$

where, *$Prob(M_i)=1$ if $M_i>0$* and *$Prob(D_i=1|M_i=1)$ if $(D_i>0|\ M_i=1)$.*

The above expression can be rewritten in the form of probability of manipulation and the conditional probability of manipulation detection as,

$$prob(M_i = 1) = \Phi(X_{M,i}\boldsymbol{\beta}_M) \tag{3-8}$$

$$prob(D_i = 1|M_i = 1) = \Phi(X_{D,i}\boldsymbol{\beta}_D) \tag{3-9}$$

where Φ represents bivariate standard normal cumulative distribution, $X_{M,i}$ and $X_{D,i}$ represents explanatory variables for the manipulation and conditional probability of detection of manipulation following Qiu (2009).

$$Prob(Z_i = 1) = \Phi(X_{M,i}\boldsymbol{\beta}_M)\Phi(X_{D,i}\boldsymbol{\beta}_D) \tag{3-10}$$

$$Prob(Z_i = 0) = 1 - \Phi(X_{M,i}\beta_M)\Phi(X_{D,i}\beta_D) \tag{3-11}$$

Equation (3-10) shows a probability of observation of a manipulation that has been detected. It is a direct extension of simple probit and can be calculated by multiplying the probability of manipulation and probability of detection of manipulation, provided it meets the condition of prior detection illustrated in Figure 3.1. Equation (3-11) is noteworthy since it captures the possibility that manipulation remains undetected (Feinstein, 1990). The likelihood and log-likelihood expression (probability of observing a sample of firms where some of them being caught as manipulator ex-post and others are not) can be denoted as

$$L = \prod_{Z_i=1}\Big(\Phi(X_{M,i}\boldsymbol{\beta}_M)\Phi(X_{D,i}\boldsymbol{\beta}_D)\Big)\prod_{Z_i=0}\Big(1 - \Phi(X_{M,i}\boldsymbol{\beta}_M)\Phi(X_{D,i}\boldsymbol{\beta}_D)\Big) \tag{3-12}$$

$$\log L = \sum_{Z_i=1} \log\Big(\Phi(\mathrm{X}_{M,i}\boldsymbol{\beta}_M)\Phi(\mathrm{X}_{D,i}\boldsymbol{\beta}_D)\Big) + \sum_{Z_i=0} \log\Big(1 - \Phi(\mathrm{X}_{M,i}\boldsymbol{\beta}_M)\Phi(\mathrm{X}_{D,i}\boldsymbol{\beta}_D)\Big) \tag{3-13}$$

The simple probit model can be estimated by following expressions

$$Prob(D_i = 1|M_i = 1) = 1 \tag{3-14}$$

$$Prob(Z_i = 1) = Prob(M_i = 1) \tag{3-15}$$

If the detection is perfect, the coefficient estimates of bivariate probit will be similar to a simple probit model (Wang, 2004).

In order to apply partial detection model of bivariate probit, the control sample firms should be non-manipulator. This study has taken due care in choosing a control sample of particularly those firms who are not in the list of SECP for any type of manipulation or fraud.

3.8.2. Firm's Propensity to Commit Fraud/Manipulation

The firm's incentive for committing fraud and manipulation are influenced by expected cost and benefit associated with it. The reduced form equation for determining incentives for manipulation is shown in (3-4). Where X_m denotes the vector of explanatory factors derived from Beneish M-Score for firms propensity to commit manipulation. ε denotes error term. A manipulator's profile as defined by Beneish (1999) is characterized by

1. rapid growth,
2. experiencing deteriorating economic conditions and
3. involved in aggressive accounting practices (Beneish et al., 2012).

Together, these eight variables can create a collective pattern of 'how a potential manipulator will look like?' Putting these eight variables from the M-Score model, the extended form of the equation (3-4) will be:

$$\begin{aligned} M_i = \beta_0 &+ \beta_1 \mathrm{Aqu\_I}_i + \beta_2 \mathrm{Sgr\_I}_i + \beta_3 \mathrm{Dsr\_I}_i + \beta_4 \mathrm{Dep\_I}_i + \beta_5 \mathrm{Sgae\_I}_i + \beta_6 \mathrm{Grm\_I}_i \\ &+ \beta_7 \mathrm{Lev\_I}_i + \beta_8 \mathrm{TaTa}_i + \varepsilon_i \end{aligned} \tag{3-16}$$

where, M_i represents a dichotomous variable indicating 1 for the firms convicted of manipulation and zero otherwise. *Aqu_I* is asset quality index representing the percentage of soft assets, Sgr_I is sales growth index, *Dsr_I* is index of days sales in receivables, *Dep_I* denotes depreciation index, *Sgae_I* is index of selling, general and administrative expenses, *Grm_I* is index of gross margin, *Lev_I* is leverage index showing financial distress of the firms, and *TaTa* denotes total accruals to total assets, thus highlighting the variation between accounting and cash profit.

Researchers have argued that firms may also manipulate their inventories. A typical motive of manipulation in inventory is to decrease the cost of goods sold, thus reporting a higher than actual gross profit. Another similar kind of manipulation involves adding bogus value for obsolete inventory (Beneish et al., 2011). COSO report confirms that inventory overstatement is the most commonly occurring form of asset misappropriation frauds (COSO, 2010). Another critical factor influencing the firm's propensity to manipulate is operating income. Operating income is an important indicator that can mislead to an investor about the financial health of the company. WorldCom, during the financial crises, started using judgements in the depreciation and amortization expenses. Since these expenses are non-cash, they are subject to manipulation and managerial judgements. Therefore, two additional variables are incorporated; *inventory overstatement Inovsst)* and *operating income to the sale* (OI/Sale) in the above M-Score equation (3-16) (Sadique, 2016).

$$M_i = \beta_0 + \beta_1 \mathrm{Aqu\_I}_i + \beta_2 \mathrm{Sgr\_I}_i + \beta_3 \mathrm{Dsr\_I}_i + \beta_4 \mathrm{Dep\_I}_i + \beta_5 \mathrm{Sgae\_I}_i + \beta_6 \mathrm{Grm\_I}_i + \beta_7 \mathrm{Lev\_I}_i + \beta_8 \mathrm{TaTa}_i + \beta_9 Inovsst_i + \beta_{10} OI/Sale_i + \varepsilon_i \tag{3-17}$$

Certain other factors also affect the firm's incentive to manipulate. Previous studies have reported that fraudulent firms are mostly in their early growth phase of the business cycle. Younger firms face enhanced pressure to meet up the earning expectations as they go for IPO, thus exhibit greater propensity of fraud. Beneish also highlighted the characteristics of manipulators as ‘typically younger firms, smaller in size and having higher growth (Beasley, 1996; Beneish, 1997; Brazel et al., 2009). Table 3.2 reports the industry classification for alleged manipulators and their matched sample. It is evident from the table that the firm's propensity to manipulate varies across the industry (Wang, 2004). Moreover, the type and nature of the industry also affects the fraud risk factors for detection of manipulation. Therefore controlling for Size (Siz), age (Age) and industry type (Indus dummy), Equation (3-17) can be written as:

$$M_i = \beta_0 + \beta_1 \mathrm{Aqu\_I}_i + \beta_2 \mathrm{Sgr\_I}_i + \beta_3 \mathrm{Dsr\_I}_i + \beta_4 \mathrm{Dep\_I}_i + \beta_5 \mathrm{Sgae\_I}_i + \beta_6 \mathrm{Grm\_I}_i + \beta_7 \mathrm{Lev\_I}_i + \beta_8 \mathrm{TaTa}_i + \beta_9 Inovsst_i + \beta_{10} OI/Sale_i + \beta_{11} Siz_i + Age_i + \varepsilon_i \tag{3-18}$$

$$M_i = \beta_0 + \beta_1 \mathrm{Aqu\_I}_i + \beta_2 \mathrm{Sgr\_I}_i + \beta_3 \mathrm{Dsr\_I}_i + \beta_4 \mathrm{Dep\_I}_i + \beta_5 \mathrm{Sgae\_I}_i + \beta_6 \mathrm{Grm\_I}_i + \beta_7 \mathrm{Lev\_I}_i + \beta_8 \mathrm{TaTa}_i + \beta_9 Inovsst_i + \beta_{10} OI/Sale_i + \beta_{11} Siz_i + \beta_{12} Age_i + \beta_{13} Indus\ Dummy + \varepsilon_i \qquad (3\text{-}19)$$

3.8.3. Factors Affecting Detection of Manipulation

One of the main objectives of the current study is the detection of manipulation and fraud. Various factors identified in fraud-related literature as 'red flags' or risk factors of fraud. These factors can be firm-specific as well as they can be industry related to which a firm belongs. Since the empirical method of this study addresses the issue of partial observability, the firm's incentive to commit fraud and detection of fraud are inter-related. Wang (2013) suggested that various factors are common in both the fraud commission and the fraud detection process. However, the direction of the relationship, might be the opposite (Wang, 2013). The simple form for manipulation detection (D_i) is represented by equation (3-5). Where X_D represents a vector of explanatory factors that can affect the probability of detection of manipulation and ε denotes error term.

The literature on corporate misconduct research reported certain factors that can trigger the analysts and other regulators for potential fraud investigation. Fraudulent firms tend to overinvest. The reasons and incentives for overinvestment may include

1) decreasing external cost of financing and
2) it can create difficulty for the analysts to correctly predict firm's cash flows (Wang, 2004).

Consequently, investment decision affects the probability of detection of manipulation. Nevertheless, unexpected performance shock will also create hype in the market for the spurious activities in the firms and can generate an investigation of fraud. CROA is used to capture the unexpected performance in the fraud detection equation.

Frauds are somehow self-revealing. Managing earnings to mislead the analysts and investors can lead to higher market expectations. If such expectations, later on, are not matched by the cash flows, they can trigger the market reaction for probable manipulation and fraud detection. Therefore ex-ante working capital accruals (WC_Accruals) is a strong determinant for the probability of manipulation detection (D_i) (Mingzi et al., 2016). Growth, profitability and inventory are also included in the fraud detection equation (Chen et al., 2006). Firms' poor performance can lead to the initial investigation and detection. Putting these variables in equation (3-5),

$$D_i = \beta_{\mathbf{0}} + \beta_{\mathbf{1}} INV_i + \beta_{\mathbf{2}} CROA_i + \beta_3 Growth_i + \beta_4 WC\_Accruals_i + \beta_5 Inven/Sale_i + \varepsilon_i \tag{3-20}$$

Where INV represents investment, CROA denotes the change in return on equity, Growth captures revenue growth, WC_Accruals shows working capital accruals of the firms, and finally, Inven/Sale is the ratio of inventory to sales. The detailed operational definition and proxies of these variables are shown in

Table 3.3.

Previous literature on fraud detection suggests that type of industry also affects the probability of detection of fraud (Ghafoor et al., 2018). The fraud risk factors also vary within a different industry. The probability of being caught is closely related to the litigation risk that the specific firm belongs. Hence adding control variables (Siz, Age and Indus Dummy), the equation (3-20) can be re-written as,

$$D_i = \beta_{\mathbf{0}} + \beta_{\mathbf{1}} INV_i + \beta_{\mathbf{2}} CROA_i + \beta_3 Growth_i + \beta_4 WC\_Accruals_i + \beta_5 Inven/Sale_i + \beta_6 Siz_i + \beta_7 Age_i + \varepsilon_i \tag{3-21}$$

$$D_i = \beta_{\mathbf{0}} + \beta_{\mathbf{1}} INV_i + \beta_{\mathbf{2}} CROA_i + \beta_3 Growth_i + \beta_4 WC\_Accruals_i + \beta_5 Inven/Sale_i + \beta_6 Siz_i + \beta_7 Age_i + \beta_8 Indus\ Dummy + \varepsilon_i \tag{3-22}$$

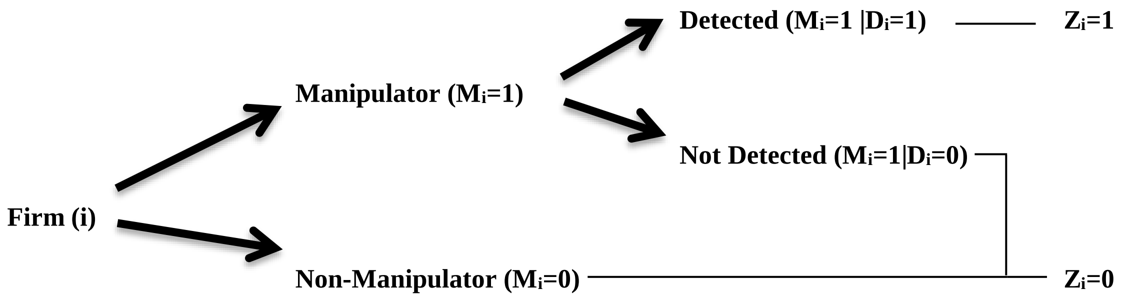

Figure 3-1: ***Partial Observability Issue*** **Source: (Wang, 2004)**

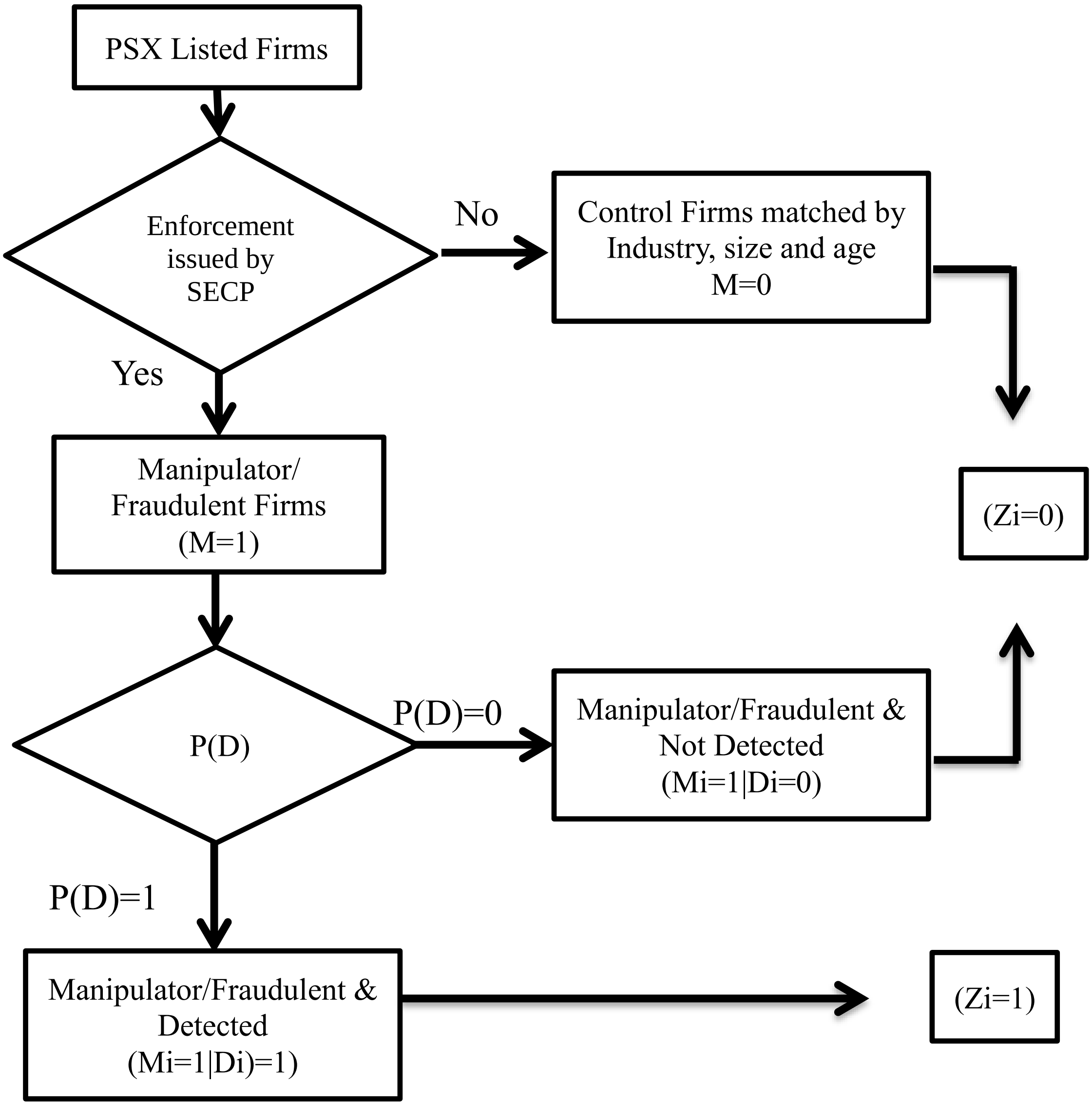

Figure 3-2: ***Flow Chart of Data and Methodology***

Source: author's compilation

4. Results and Discussion

4.1. Introduction

This chapter presents a detailed explanation and results of the statistical analysis of the data. The study will present the overall feel of the data by highlighting inferential statistics. Inferential statistics will include univariate analysis of the manipulator sample firm and the discussion. Additionally, univariate analysis of control firm is also presented to highlight the difference between manipulator firms and their corresponding control firms. It involves a comprehensive analysis and comparison of descriptive statistics of manipulator versus non-manipulators firm-year (of manipulators) data based on their mean, median, t-test, Mann-Whitney test and test of the median. This chapter continues comparing manipulator and non-manipulator firms based on their inferential statistics. Probit regression is used as an analysis technique first to identify M-Score attributes and their differences in determining manipulator firm and non-manipulator firms. The issue of partial observability of the manipulator is addressed by applying bivariate probit analysis. Bivariate probit model will distinguish the firm's propensity to manipulate and the conditional probability of detection of manipulation (Beneish et al., 2012; Wang, 2013).

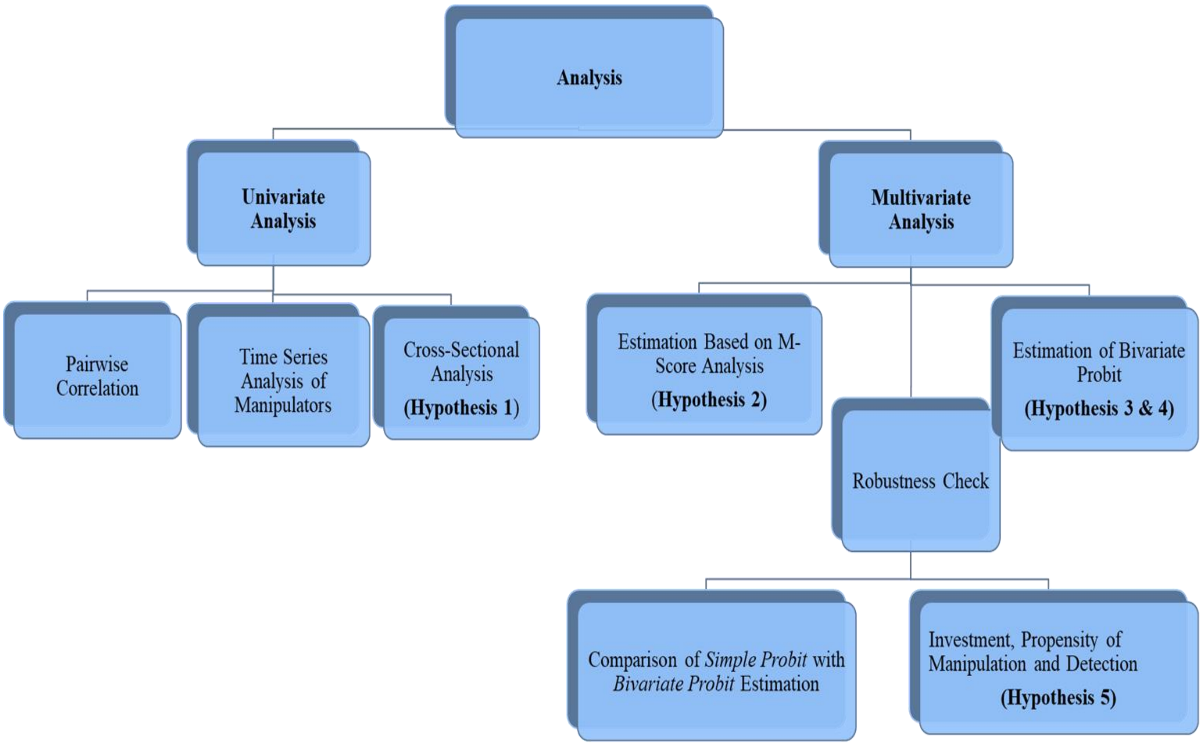

Figure 4-1: ***Sequence of Results***

Source: Author's compilation

4.2. Overview of the Sample

This study includes manipulator firm; those chosen on the basis of enforcement release of SECP, and a sample of control firms matched on the basis of criteria mentioned in chapter 3. The procedure for selection of control sample is mainly based on the SIC classification and size among other factors.

Table 4.1: Comparison of TOTAL ASSETS (Thousands of PKR) of Manipulator and Control Firms

	Manipulator	Non-Manipulator
Mean	3827013	4114597
Minimum	189821	199820
Maximum	1.50e+07	1.45e+07
Difference in Mean	287584.3	
T-statistic	0.7014	
Mann-Whitney test (Z)	0.694	
Median Test (χ^2)	0.9434	

Source: Based on the author's calculation

In Table 4.1, descriptive statistic of total assets of manipulator and non-manipulator firms (in thousands of PKR)[5] is presented. Since total assets (Size is 'log of total assets') is the deciding factor for choosing the sample firms, we test their mean difference and Mann-Whitney test to analyze the difference between these two groups. The result of the non-parametric test indicates that there is no difference (value of Z and Chi-square is insignificant) between a sample of manipulator and control firm with regards to their total assets. It is very crucial for this study to realize that the sampling technique used for identifying control firms is reliable and further sophisticated testing and analysis will lead us to our expected results without any bias.

4.3. Univariate Analysis

This section will present a univariate analysis of manipulator and control firms. The univariate analysis includes pairwise correlation analysis, descriptive statistics, testing mean differences using t-statistics and non-parametric test of Wilcoxon Sign Rank and Median test. Non-parametric tests are carried out to analyze the difference between manipulators and control sample firms on various attributes. The motivation for carrying out univariate analysis

[5] PKR is the currency in Pakistan. The acronym stands for Pakistani Rupees.

is to determine overall '*feel*' of the sample and compare the differences between *the test sample* (firm issued enforcement) and *control sample*.

4.3.1. Pairwise correlation

The first stage of analysis involves testing the statistical correlation between all sets of variables involved in the testing. The correlation matrix will provide a summary of all expected relation between independent and dependent variables (Turvey, 2012). Table 4.2 reports a pairwise correlation of dependent variable *M (1 for manipulator and zero for non-manipulator),* correlated with the determinants of M-score, other independent variables (to be used for further analysis of the probability of detection of manipulation) and control variables. All manipulator-control firm-year observations (total 602) are used to determine the correlation between independent *M* and sets of independent variables in this testing. Correlation analysis is carried out to determine the *strength* and *direction* of the relationship between independent variables. The correlation coefficient (r) and their significance (p-value) are reported in the table. The statistically significant ($p<0.01$) and positive correlation between M-Score indices and dependent variable M shows that these variables affect each other and further analysis is mandatory to test their relationship (Hasan, Omar, Barnes, & Handley-Schachler, 2017). Two out of eight variables of M-score (0.01) and positive correlation between indices and dependent variable (M) show that these variables affect each other.

The analysis is mandatory to test their relationship (Hasan et al., 2017). Two out of eight variables of M-Score show a partial negative correlation with the dependent variable. The control variables (SIZ and AGE) are positively ($p<0.01$) and partially positively correlated with the dependent variable.

For M-Score variables, Aqu_I has significant and positive correlation with Dsr_I (*$r=0.0681$ and $p< 0.1$*), Dep_I (*$r=0.1068$ and $p<0.01$*) and Lev_I (*$r=0.2344$ and $p<0.01$*), whereas it has significant negative correlation with TATA ($r=-0.0877$, $p<0.05$) and Inven/Sale ($r=-0.0773$, $p<0.05$). The second variable in M-Score shows a significant and positive correlation with SIZ and significantly negative correlation with AGE. These findings corroborate to the results of Beneish, Lee, and Nichols (2012) who reported that manipulators firms, mostly on the maturity stage of their business cycle, and are characterized by high sales growth index.

Table 4.2: Pairwise Correlation of Manipulators-Control Firm-Year Observations

Independent Variables	M	Aqu_I	Sgr_I	Dsr_I	Dep_I	Sgae_I	Grm_I	Lev_I	TATA	Inven_ovsst	OI/Sale	INV	CROA	GROWTH	WC_Accr	Inven/Sale	SIZ	AGE
M	1																	
Aqu_I	-0.0046	1																
Sgr_I	0.2799***	-0.0447	1															
Dsr_I	0.3628***	0.0681*	-0.2604***	1														
Dep_I	0.0862**	0.1068***	-0.0756*	0.0511	1													
Sgae_I	-0.1010***	0.023	-0.4604***	0.2205***	0.0772**	1												
Grm_I	0.1579***	-0.0224	-0.1194***	0.0154	-0.0686*	0.0367	1											
Lev_I	-0.04	0.2344***	-0.0921**	0.1255***	-0.1404***	0.114***	-0.0047	1										
TATA	0.3300***	-0.0877**	0.2024***	-0.0797**	-0.0189	-0.1813***	0.0166	-0.0866**	1									
Inven_ovsst	0.1097***	-0.0478	0.2281***	-0.0584	-0.088**	-0.1071***	0.0611	-0.0141	0.1769***	1								
OI/Sale	0.0862**	0.0149	0.0481	0.0539	0.0359	0.001	0.0739*	0.0114	-0.0172	-0.0297	1							
INV	0.0332	-0.0286	-0.0112	0.0382	0.0248	-0.0462	0.0042	0.0108	0.0279	-0.0228	0.0187***	1						
CROA	0.0013	-0.0319	-0.0026	-0.0212	-0.0105	-0.0202	0.0445	-0.0103	0.0274	0.0103	-0.0133	0.0066	1					
GROWTH	-0.0313	-0.0344	-0.0015	-0.0509	0.0293	-0.0103	0.0425	-0.0142	0.1185	0.0021	0.0196	-0.0047	0.0004	1				
WC_Accr	0.018	0.0134	-0.0185	0.0299	0.0114	-0.0448	0.0057	-0.0222	0.2343***	0.0182	0.0123	0.0412	-0.0142	-0.0271	1			
Inven/Sale	-0.1268**	-0.0773**	-0.0525	-0.0823**	-0.0013	0.0797**	0.0277	0.0096	0.0103	0.0391***	-0.3428***	-0.1235***	0.3631	0.3631	-0.0208	1		
SIZ	0.3601***	0.0412	0.0951***	0.1547***	0.0372	-0.0218	0.0374	-0.012	0.1185***	0.0057	0.0043***	-0.0292	0.0082	0.0082	0.2184	-0.1435***	1	
AGE	0.0243	-0.0542	-0.0850**	0.0474	-0.0072	0.0565	0.0022	-0.0217	0.0267	0.0309***	0.0813**	0.0187	0.003	0.003	0.0495	0.0258	0.0043	1

Note: Correlation coefficient (r) and their significance level (denoted by ***, ** and * representing significance at 1% 5% and 10% level of significance respectively) are reported against explanatory variables and control variables (Source: Author's calculation)

Sgr_I has a negative and significant correlation with all variables of M-Score except TATA, where it shows a significant positive correlation ($p<0.01$). From control variables, Sgr_I is negatively correlated ($p<0.05$) with AGE of the firm. Dsr_I has a positive to a partially positive correlation with most of the indices of M-Score.

Additionally, Inven_ovsst shows a partial negative correlation with most of the M-Score predictors while OI/Sale partial positive correlation with M-Score predictors except TATA. Generally, M-Score variables show a partial negative correlation with other variables. With control variables, M-Score indices show a significant positive correlation (SIZ). However, with AGE, M-Score indices show a mixed trend of Partial negative to a significantly positive correlation. Correlation is an essential indicator for testing the collinearity issue of the variables. From Table 4.2, it is evident that none of the correlation coefficients has a value higher than the threshold value.

4.3.2. Time Series Analysis of Manipulators

This section explains the analysis of misstating firms that have been issued enforcements by SECP. It includes comparing the year identified as fraud year t to other years of all manipulator firms. Table 4.3 analyzes the mean of the manipulator and non-manipulator years, the mean difference between the manipulator and non-manipulator year, Wilcoxon Sign Rank test and median comparison. The last two non-parametric statistics account for pairwise comparison of the manipulator/ and non-manipulator year by assuming *the null hypothesis* of no difference between the groups. Thus each manipulating firm is compared directly to itself by comparing the year identified by SECP as manipulation year to all other year used for analysis. The results show that manipulators firms have significantly higher mean value (for four out of eight indices of M-Score) in the manipulation year as compared to non-manipulation years. Mean value of Sgr_I, Dsr_I, Grm_I and TATA are significantly higher at manipulation year than other years. This is evident from the significant positive value of mean differences, analyzed using t-test statistics. SIZ is significantly smaller for the firms for manipulation year than other years used in the analysis. It shows that most of the firm issued enforcements in the earlier years of their business cycle. Since every firm is compared to itself, it led to reduction in the number of observation used in the calculation of t-statistics.

However, this analysis is advantageous in a way that it could serve to weigh the observations used in the analysis accurately. The results of Wilcoxon Sign Rank show that most of the variables analyzed are significantly different in manipulation year and other years. This analysis is appropriate for comparing the sample and matching them on specific criteria. The Median test compares the median value of manipulation and non-manipulation year; whereas the significant value of Chi-squares leads to conclude that the test parameters are significantly different from each other. These tests compare the characteristics of manipulators firms and match the distribution of manipulation year and other years. The reported p-values call for the rejection of the null hypothesis of no difference (Beneish, 1999b).

Table 4.3: Descriptive Statistics for the Firms Subject to SECP Enforcement

	Year of manipulation			Year of non-manipulation			Manipulation VS non-manipulation year				
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Difference in Mean	P value	t-stat	Wilcoxon-Z (P-Value)	Median_Chi^2 (P-Value)
Aqu_I	95	1.01299	0.10922	139	1.01597	0.08522	0.0033	0.8148	0.2345	0.507 (0.6124)	0.2866 (0.592)
Sgr_I	95	1.2599	1.2599	139	0.93709	0.377862	-0.3230	0.000	-5.3987	4.858 (0.000)	18.3417 (0.00)
Dsr_I	95	1.62825	1.1259	139	0.94237	0.644017	-0.6858	0.000	-5.9204	-4.933 (0.000)	23.6946 (0.00)
Dep_I	95	1.0297	0.3115	139	1.02434	0.25381	-0.00536	0.8855	-0.1442	0.075 (0.9400)	0.0179 (0.118)
Sgae_I	95	1.0588	0.75143	139	1.2110	0.65451	0.15222	0.1027	1.6384	2.723 (0.001)	10.2773(0.001)
Grm_I	95	0.8411	0.9140	139	0.551628	0.78764	-0.2895	0.0106	-2.5766	-2.423 (0.004)	3.5107 (0.061)
Lev_I	95	1.0235	0.2901	139	1.04836	0.25093	0.02481	0.4880	0.6946	0.474 (0.6355)	0.0179 (0.844)
TATA	95	0.00416	0.08132	139	-0.06461	0.0767	-0.0687	0.000	-6.5425	-6.549 (0.00)	34.677 (0.00)
Inven_ovsst	95	0.059341	0.3124	139	0.18672	0.7016	-0.01107	0.7969	-0.2577	-0.508 (0.6112)	0.0997 (0.752)
OI/Sale	95	-0.11707	0.3686	139	-1996.152	10583.43	-1996.03	0.0720	-1.8076	-2.191 (0.0284)	1.9409 (0.164)
INV	95	2.87e-07	3.22e-06	139	-1.10e-06	9.38e-06	-1.39e-06	0.1740	-1.3637	-2.901(0.00)	9.0085 (0.003)
CROA	95	0.672249	7.98606	139	0.16597	9.7953	0.6793	-0.4140	-1.7471	-1.249 (0.2118)	1.9409 (0.164)
GROWTH	95	0.9910	9.0758	139	6057.615	72173.12	6056.615	0.4220	0.8043	1.511 (0.1307)	1.1464 (0.284)
WC_Accr	95	22.286	140.3431	139	49.809	226.1026	27.5229	0.2994	1.0403	-0.425 (0.6705)	0.0716 (0.789)
Inven/Sale	95	0.20581	0.3290	139	0.187977	0.35116	0.0684	0.0680	1.4964	4.112 (0.00)	23.2137(0.00)
SIZ	95	13.76247	2.0547	139	15.1289	1.5065	-1.44706	0.00	-0.4880	1.511 (0.00)	18.3417(0.000)
AGE	95	27.02174	10.586	139	25.694	10.1948	-1.69075	0.2163	-1.2399	-1.276 (0.2019)	1.3829 (0.016)

Note: *This table presents the mean and standard deviation of Manipulators by comparing the year of manipulation with other years. It also explains the difference in the mean by conducting the t-test. Wilcoxon sign rank statistics and median χ^2 with their p values are also reported. Every manipulating firm is compared to itself directly. In order to remove the extreme values, data is wonsorized at 1% and 99% using STATA. (Source: based on author's analysis)*

Source: author’s estimation

4.3.3. Cross-Sectional Analysis of Manipulators versus Control Firms

Table 4.4 compares all manipulator firm-year observation to the control firm-year observations, matched to the manipulators based on characteristics discussed in chapter 3. The table reports the mean and standard deviation of control and manipulator firms. T-statistics are also reported to compare the mean differences between the groups. The objective of this univariate analysis is to identify and compare the characteristics of manipulator firms against the number of control firms and to test the null hypothesis *of no difference in manipulators and control firms* against these attributes.

The results of assets quality index shows that mean Aqu_I for manipulators is significantly higher than mean asset quality index for non-manipulators (control firms). This difference is evident from significant p ($p<.10$) value of t-statistics. Wilcoxon Sign rank test also gives a significant difference between these two groups based on significant Z-value ($p<.10$). The result of univariate analysis for Aqu_I confirms that manipulators and control firms are significantly different from each other concerning their assets quality index. The support for this results can be obtained from the results of Dechow, Ge, Larson and Sloan (2011) who found a higher percentage of soft assets in the manipulating firms than other Compustat sample firms. The higher net operating assets provide managers more discretion in the form of accounting flexibility to report a higher-than-actual earning.

Nevertheless, a higher value of Aqu_I points to the managerial discretion of cost deferral and it leads to the reduction in the expenses. Such changes lead to the activities for reporting income increasing earning management. Consequently, a higher than 1 value of Aqu_I indicate the involvement of the firm's management in asset overstatement (Dikmen & Küçükkocaoğlu, 2010).

Sales growth index shows a higher mean value for the group of manipulators compared to non-manipulator (control firms). The t-test statistics and univariate analysis show that the groups are significantly different (null hypothesis is rejected) than each other as the p-values of tests are less than 0.05. The results are not surprising since the general characteristics of manipulators, as described by ACFE, are high growth firms as the financial position and capital requirement put these companies under pressure. A higher than 1 value of Sgr shows that the firm is exhibiting positive sales growth over the years (Anh & Linh, 2016).

Table 4.4: Descriptive statistics for Control firm-Year and Manipulators Firm–Year Observations for Sample Period

	Control Firm-Year			Manipulator Firm-Year			Control VS Manipulators Firm-Year				
Variable	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Difference in Mean	P value	t-stat	Wilcoxon-Z P-Value	Median χ^2 P-Value
Aqu_I	367	1.0008	0.0957	234	1.0148	0.0947	-0.0139	0.0819	-1.7427	-1.687 (0.0916)	2.3232 (0.127)
Sgr_I	367	1.0320	0.46504	234	1.0640	0.4729	-0.0319	0.0414	-0.8169	-0.834 (0.4040)	0.2857 (0.593)
Dsr_I	367	1.2463	0.94984	234	1.2120	0.9267	0.0343	0.6628	0.4363	0.283 (0.7773)	0.0062 (0.979)
Dep_I	367	1.0414	0.2750	234	1.0264	0.2773	-0.2186	0.014	0.6488	0.893 (0.3719)	3.9013 (0.0427)
Sgae_I	367	1.2211	0.7055	234	1.1512	0.6967	0.0699	0.2349	1.1891	1.542 (0.1230)	2.6914 (0.101)
Grm_I	367	0.8058	0.82097	234	0.6654	0.8496	0.14037	0.0442	2.0162	2.077 (0.0378)	4.5902 (0.032)
Lev_I	367	1.0218	0.82026	234	1.0386	0.2667	-0.0168	0.4438	-0.7663	-0.888 (0.3747)	0.2857 (0.593)
TATA	367	-0.0352	0.0855	234	-0.0376	0.0853	0.00238	0.7395	0.3326	0.191 (0.8482)	0.0400 (0.842)
Inven_ovsst	367	0.1252	0.6418	234	0.05263	0.3202	0.0969	0.0542	1.6078	-0.457 (0.6479)	3.0875 (0.079)
OI/Sale	367	-2211.16	12419.32	234	-1208.02	8279.35	-1003.14	0.2769	-1.0884	0.550 (0.5821)	1.9381 (0.164)
INV	367	-1.55e-07	7.55e-06	234	-1.11e-07	7.13e-06	-4.37e-08	0.9438	-0.0705	0.473 (0.6362)	0.2541 (0.614)
CROA	367	-0.1938	7.5738	234	0.3658	9.1092	-0.5596	0.4173	-0.8118	-0.148 (0.8823)	0.0480 (0.827)
GROWTH	367	2957594	3957292	234	3821270	4647731	-863675.5	0.0152	-2.4338	-2.120 (0.0340)	7.3417 (0.000)
WC_Accr	367	-41187.57	938381.5	234	-18052.85	912371.4	-23134.72	0.7660	-0.2977	-0.320 (0.7490)	0.7006 (0.403)
Inven/Sale	367	0.16108	0.3715	234	0.19435	0.3425	-0.0333	0.0018	1.1034	6.278 (0.00)	44.35 (0.000)
SIZ	367	14.2083	2.0831	234	14.332	1.4862	-0.1233337	0.4630	-0.7344	-0.573 (0.5686)	0.4926 (0.483)
AGE	367	26.8065	10.5270	234	25.996	10.2003	0.8108	0.3518	0.9318	0.860 (0.3898)	0.8211 (0.365)

Note: The proxies and explanations for all the variables in this table have been discussed in chapter 3, table 3.3. All the variables are continuous variables, winsorized at 1% and 99% to remove extreme values. Source: Base on author's own calculation

Source: author's estimation

Hence, growth companies exhibit higher incentive to commit fraud (Abbasi et al., 2012). Days' sales in receivables index are slightly higher for control firm as compared to mean Dsr_I in the case of manipulator group. However, the univariate analysis of the group shows that there is no difference between Dsr_I of manipulators and Dsr_I of non-manipulators (control firms). Empirical studies, conducted in fraud-related research, suggest the higher value of Dsr_I for the firms accused of manipulation. Firms, who are typically involved manipulating revenue by adding false receivables, usually end up having higher Dsr_I value (Sadique, 2016).

Depreciation index has significantly higher mean value for control firms than manipulator sample firms. The value of t statistic is significant ($p<0.01$), thus suggesting that mean Dep_I for the manipulator is different from control firms. The results of the univariate analysis of the median test also suggest that both groups are significantly different from each other ($\chi^2=3.90$, $p<0.05$). It is important to note that both manipulators and control group have higher than 1 value of their Dep_I. Both manipulator and control firms have lowered the rate at which their assets depreciated over time. It can be done by adopting a new method of depreciation or by making an upward shift in assets' useful life (Beneish, 1999).

The mean value of sale, general and administrative expenses index for the control group is slightly higher than the manipulator. However, the mean difference is not significant suggesting that the value of Sgae_I for manipulator and the control group is not significantly different. The results suggest that both groups are similar to each other in term of their Sgae_I. These findings corroborate to the finding of Dikmen & Küçükkocaoğlu (2010) who reported that manipulating firm exhibit disproportionate changes in the relation of selling, general and administrative expenses to sales. These expenses vary according to the changes in sales of the firm. A higher than 1 value indicates that revenue overstated and expenses are understated.

The mean value of gross margin index for control sample is higher than the mean value of Grm_I for manipulators. The results of the univariate analysis also confirm the significant difference of Grm_I of the two groups. The value of t-test statistics is significant ($p<0.05$), which confirms that both groups have significantly different mean value for Grm_I for the studied period. Similarly, the results of Wilcoxon Z-test ($p<0.05$) and median χ^2 test also confirms that gross margin index of both groups is significantly different from each other.

A gross margin index higher than one shows that the company may have deteriorating financials, which can give firm an incentive to manipulate. In this study, however, none of the samples has a gross margin index higher than one. One argument to this scenario could be the involvement of firms (especially manipulators) in income increasing earning management (Sadique, 2016). It is contrary to the findings of (Beneish & Nichols, 2005; Repousis, 2016).

The result of Lev_I shows that manipulator firms are more levered as compared to the control sample firms. The mean value of Lev_I for the manipulator is 1.03 against the mean value of Lev_I for the control group, which is 1.02. The results of univariate analyses show that the manipulator and control firms are not different in term of their Lev_I. It is evident from the insignificant value of Wilcoxon Z and χ^2 value. Likewise, the mean difference value, as suggested by the t-test, also confirms that both groups have no difference in their Lev_I. Studies suggest that the Lev_I greater than one signals that the debt level has increased (Cecchini, Aytug, Koehler, & Pathak, 2010). LEV_I higher than one suggests that the firm is manipulating its assets without changing its capital structure. Firms with high leverage have greater propensity to commit fraud since they feel pressure caused by strict debt covenants. Manipulator firms, as suggested by Beneish (1997) are characterized by high leverage and growth (Beneish, 1997).

The mean TATA for manipulators is lesser than mean TATA for non-manipulators. The t-test suggests that the mean difference between TATA of both groups is the same. The result of univariate analysis rejects the possibility of difference between the groups on the basis insignificant values of Z and χ^2. TATA captures the extent to which cash and reported earnings differ than each other. A higher positive value of TATA suggests the possibility of manipulation. The results suggest that the TATA value of manipulators is slightly smaller than that of the control group (Anh & Linh, 2016).

The result for inventory ratio suggests that the manipulator group has lower inventory ratio as compared to the control sample firms. The t-test reveals a significant difference between the mean values of both groups concerning this ratio. It is evident from the significant value of t statistics ($p<0.10$). Further examination of results leads us to conclude that both groups are not different in their mean ranks, as suggested by Wilcoxon Z-statistics. Contrarily, the median test of the inventory ratio highlights the significant difference between the median of both groups. The hypothesis of no difference between the manipulators and control firms with regards to their inventory ratio can be partially rejected. The ratio highlights the possibility of overstatement in inventory to decrease the cost of goods sold (CGS), thus revising gross margin in upward direction (Cecchini et al., 2010).

Further, the result of operating margin shows that manipulators have less negative operating profit margin as compared to the group of control firms. The test of the mean also suggests that the manipulator and the control group are similar as far as their operating margin is concerned. The result of univariate analysis also rejects the possibility of difference between ranks and median of manipulators and control, evidenced by insignificant Z and χ^2 values. Research in the related field suggests that manipulating firms often inflate their operating profit margins by adding fictitious revenues without any subsequent increase in their cost. It can cause an operating profit to inflate and reach the bottom line (Abbasi et al., 2012).

For other variables, the manipulator and control group show mixed results. For instance, fraudulent firms outperform the control group in term of the mean value of investment intensity. The result of t-test for INV suggests that the mean difference is not significant between these groups. Moreover, the results of the univariate analysis also suggest that both manipulators and control are not different from each other. A higher mean for the manipulator is confirmed by previous empirical studies which reported that fraudulent firms tend to make overinvestment in order to gain short term overvaluation (Wang, 2004). Overinvestment helps the firm to extract the investors' attention on cash flows estimates, and makes fraud detection process comparatively harder. The mean CROA for the manipulator is higher than mean CROA for the control group. CROA measures unexpected performance shock. Univariate analysis of CROA also enables to conclude that both group exhibit no apparent differences concerning their CROA ($P>0.1$). Fraudulent firms are expected to have higher performance shock to hide the deteriorating fundamentals (Dechow et al., 2012). Manipulator firms are characterized by high growth (Ashraf, 2011) and measured by a change in sale revenue over the years. The results also confirm that the manipulators outperform control sample in term of mean growth. The difference in mean Growth is significant ($p<0.05$). The result of univariate analysis reveals that the manipulator and non-manipulators (control groups) differ significantly from each other. The significant Wilcoxon and median test ($p<0.01$) reject the null hypothesis of no difference. Misstating firms have higher working capital accruals as compared to the control group, which have a more negative value of WC_Accr. The mean difference of accruals between the groups is not significant. Similarly, the result of univariate analysis also leads to the conclusion that both groups have the same working capital accruals. The results validate the findings of previous studies, who found that overinvestment could be one of the possible reasons for higher accruals in misstating firms (Dechow & Dichev, 2002; Dechow et al., 2011).

Inven/Sale ratio is slightly higher for manipulators as compared to control firms. The results show that the difference in mean value is significant. Moreover, the Z-value and χ^2 values confirm that both groups are different from each other concerning their Inven/Sae. Similar results presented by Rosner (2003). The higher Inven/Sale for manipulators suggests that inventory is growing faster than the sale. It could be a sign of potential manipulation in the firms (Rosner, 2003; Sadique, 2016).

The results of the control variables show that manipulators are typically larger in size as compared to control sample firms. The difference in mean is not significant (p>0.1). Moreover, both groups are not significantly different from each other, as evidenced by higher p values value of both Z and χ^2 tests. The same results supported by Dechow et al. (2011). One of the possible explanations to this could be the fact that large firms face stricter scrutiny from regulators. Hence, their probability of being caught is higher (Brazel et al., 2009) than the others. Manipulators are slightly younger than their matched control firms. The mean AGE of manipulator and control is 25 years and 26 years, respectively. However, the mean difference and the group difference between them are not significant. The argument behind this result could be the possibility that control firms were matched in AGE to the manipulators in the process of selecting control sample (detailed explanation in chapter 3).

Concluding remarks

This study analyzed and tested the attributes of M-Score and other variables used in the analysis of predication of manipulation. The general behavior of the test sample and control firms is analyzed in order to compare and contrast the difference between the sample firms against these attributes. Mean and standard deviation of both sample and control firms are reported. For the purpose of testing the hypothesis 1 (H1), T-test is also reported. The results showed that M-Score variables are significantly different from each other: especially p values for Aqu_I, Sgr_I, Dep_I and Grm_I are less than 0.1, thus suggesting that both groups are significantly different from each other. From these results, it is concluded that sub-hypotheses i.e., *H1a, H1b, H1d, H1f* are fully supported. However, *H1c, H1e, H1g* and *H1h* are not supported based on results (p>0.1 for Sgae_I, Dsr_I, Lev_I and TATA). Apparently, out of eight indices of M-score, four indices depict significant difference for the manipulators and the control sample firms. Hence we can partially accept *H1 (Manipulators and control firms are differ than each other with respect to their M-Score indices).*

4.4. Multivariate Analysis

The multivariate analysis comprises of three stages. In the initial stage, the M-Score baseline model is analyzed by comparing the sample of manipulators and control firms. It is done in order to test the following (H2) hypothesis; '*There is a positive relation between M-score indices and firm's propensity to manipulate'*.

In this model, the dependent variable is represented by letter M, which is a binary variable representing 1 for the group of manipulators and zero for control firms, matched to manipulators based on size, age and industry classification. In the second stage of multivariate analysis, a bivariate probit model is tested, capturing the firm's propensity to manipulate and a conditional probability of detection of manipulation in a simultaneous-setting. In the third stage, the results of the bivariate probit model are compared with simple probit regression to validate the suitability of the model (Wang, 2011).

4.4.1. Estimation Results Based on M-Score Analysis

Table 4.5 presents the probit model estimation of manipulators and control firms to analyze how Beneish M-Score indices can successfully predict the firm's propensity to manipulate. For that purpose, the dependent variable *M*, representing manipulation, is estimated using the primary model presented by Beneish (1999). The results of all the model shows that Wald χ^2 estimates of all the models are significant ($p<0.01$), thus indicating that all the analyzed models have significant power. Appropriate Pseudo R^2 values confirm the descriptive validity of all the analyzed models. In order to determine overall models' Goodness of Fit (GOF), Hosmer-Lemeshow test is conducted. χ^2 values with their significant level are present at the end of table. Model *3* and model *5* show the best fit according to the Hosmer-Lemeshow GOF test ($p>0.05$).

The p-value for Hosmer-Lemeshow χ^2 should be greater than 0.05 (Hosmer & Lemeshow, 2000). The other way to check overall model-fit is through classification accuracy, reported in *Table 4.6*. Model 3 and model 5 shows the highest classification accuracy of manipulators and control firms in all the estimation of probit. Moreover, the type-II error is also lowest for them.

Table 4.5: Probit Estimation of Manipulator-Control-Firm-Year Observations Using M-Score Indices

Variables [a]	Model 1	Model 2	Model 3	Model 4	Model 5
			Dependent Variable *M*		
Aqu_I	0.9641	0.7213	0.9407	0.8828	0.9276
	(0.8134)	(0.8400)	(0.9152)	(0.8167)	(0.9041)
Sgr_I	2.3475***	2.1068***	2.3025***	2.3440***	2.2967***
	(0.3362)	(0.2433)	(0.3223)	(0.3406)	(0.3260)
Dsr_I	1.4163***	1.1264***	1.1681***	1.4197***	1.1636***
	(0.2211)	(0.1223)	(0.1739)	(0.2225)	(0.1728)
Dep_I	0.8802***	0.6550***	0.7828***	0.8596***	0.7738***
	(0.2459)	(0.2960)	(0.3012)	(0.2477)	(0.3011)
Sgae_I	-0.1013	-0.0833	-0.0665	-0.1172	-0.0767
	(0.1613)	(0.1212)	(0.1518)	(0.1618)	(0.1516)
Grm_I	0.8506***	0.7144***	0.7788***	0.8548***	0.7798***
	(0.1221)	(0.1104)	(0.1311)	(0.1235)	(0.1317)
Lev_I	-0.37035	-0.4625	-0.4541	-0.3825	-0.4595
	(0.3362)	(0.3144)	(0.3514)	(0.34213)	(0.3480)
TATA	7.8941***	4.67e-07***	5.66e-07 ***	7.9678***	5.64e-07 ***
	(1.2620)	(6.92e-08)	(8.00e-08)	(1.2661)	(8.00e-08)
Other Variables					
Inven_ovsst				-3.63e-08	-3.81e-08
				(1.21e-07)	(1.41e-07)
OI/Sale				0.00002**	6.02e-06
				(8.53e-06)	(6.80e-06)
Siz			0.3750***		0.3745***
			(0.0519)		(0.0510)
Age			0.3752**		0.3635**
			(0.1784)		(0.1830)
Indus Dummy	*NO*	*YES*	*YES*	*NO*	*YES*

Constant	-6.3904***	-6.3771***	-13.77***	-6.2047***	-13.64***
	(1.04243)	(1.0081)	(1.6655)	(1.0484)	(1.6597)
Wald χ^2 (*d. f.*)	91.20*** *(8)*	565.6***(18)	513.55****(20)*	90.37****(10)*	528.49*** (22)
Log pseudo-likelihood	-220.76	-192.60	-160.74	-217.10	-159.787
Pseudo R^2	0.4505	0.5206	0.5999	0.4529	0.5973
Hosmer-Lemeshow χ^2	120.28***	21.05***	12.99	118.40***	7.40

Notes: This table presents the baseline model of Beneish M-Score (chapter 3, equation 2) with additional variables (equation 3, 4 and 5). We also present results by controlling firms' size and age. The dependent variable in this model is M, which is a binary variable representing 1 for manipulators (firms issued enforcement by SECP) and zero for non-manipulators/control sample. The operational proxies for all the indices and variables used in this model explained in chapter 3, Table 3.3. Indus Dummy is a dummy for capturing industry-effect, based on 2-digit SIC industry classification of the sample. Robust standard errors are presented in parenthesis. ***, ** and * show significance level at 1%, 5% and 10% respectively
Source: Based on the author's estimation and analysis

Estimating the manipulators, five out of eight M-Score variables give significant results throughout in all the five models analysed. The result of Aqu_I is positive, thus showing a probability of change in accounting treatments for cost deferral. However, the insignificant *p*-value leads to conclude that the asset quality index does not affect the firm's propensity to manipulate. The result for Aqu_I remains unchanged in the entire models predicted. The coefficient for Sgr_I is positive with the p-value less than 0.01. It is consistent with the fact that growing companies have a higher likelihood of manipulation and fraud. The result for Sgr_I is consistent in the entire analysis (from model 1 to 5).

A positive (1.4163) and significant coefficient of Dsr_I ($p<0.01$) suggests that manipulators have higher value of Dsr_I as compared to control firms. It is noteworthy that value of Dsr_I is higher than 1, thus confirms that manipulating firms revise their receivables upward disproportionately, and have a higher probability of manipulating sales revenue (Beneish, 1999). Similarly, the result of Dep_I is positive with the significant coefficient of 0.8802 ($p<0.01$). The result remains unchanged as we move from *model 1* to *5*. Consistently, manipulating firms have higher depreciation, that is achieved by either changing method or increasing assets' useful life (Tarjo & Herawati, 2015). It is inconsistent to initial findings of Beneish, where Dep_I was positive but insignificant in all the tested models (Beneish et al., 2012).

Table 4.6: ***Classification Accuracy of Manipulator-Control-Firm-Year Observations Using M-Score Models (from Table 5)***

	Model 1			**Model 2**			**Model 3**		
	Predicted			*Predicted*			*Predicted*		
Actual	Manipulator	Control	Total	Manipulator	Control	Total	Manipulator	Control	Total
Manipulator	**187**	47	234	**195**	39	234	**197**	37	234
Control	36	**331**	367	41	**326**	367	37	**330**	367
Total	234	378	**601**	236	365	**601**	234	367	**601**
Manipulator	**79.91%**	20.08		**83.33**	16.66		**84.18%**	15.81%	
Control	9.8%	**90.19%**		11.17	**88.82**		10.08%	**89.91%**	
Percentage of Correct Classification		**86.19%**[a]			**86.68%**			**87.68%**	
Sensitivity		**79.91%**[b]			83.33%			**84.18%**	
Specificity		**90.19%**[c]			88.82%			**89.91%**	
Type-I error		**9.8%** [d]			11.17%			10.08%	
Type-II error		**20.08%**[e]			16.67%			15.81%	

	Model 4			**Model 5**		
	Predicted			*Predicted*		
Actual	Manipulator	Control	Total	Manipulator	Control	Total
Manipulator	**186**	47	233	**196**	37	233
Control	33	**326**	359	36	**323**	359
Total	219	373	**592**	232	360	**592**
Manipulator	**79.82%**	20.17%		**84.12%**	15.87%	
Control	9.19	**90.8%**		10.02%	**89.97%**	
Percentage of Correct Classification		**86.48%**			**87.67%**	
Sensitivity		**79.82%**			84.12%	
Specificity		**90.8%**			**89.97%**	
Type-I error		**9.19%**			**10.02%**	
Type-II error		**20.17%**			**15.87%**	

Note: Source: based on the author's calculations.

[a] *correct classification* is calculated as (187+331/601). [b] *Sensitivity* is calculated as (187/234). [c] *Specificity* is calculated as (331/367). [d] *Type-I error* is calculated as (36/367) [e] *Type-II* is error calculated as (47/234).

Result for the Grm_I is positive with coefficient 0.8506 and significant ($p<0.01$) throughout the estimation. The result can be supported by the argument that a higher Grm_I captures the worsening performance of the firm over time. Hence, such firms have greater incentive to manipulate (Repousis, 2016). The coefficient of total accrual to the total asset is positive and significant at $p<0.01$. The positive accrual coefficient confirms that manipulators have less cash than their accounting profit figures, and involved in a fraudulent act. The result of Sgae_I and Lev_I shows that they have negative coefficient, however, result is insignificant suggesting that they have no impact on firm's incentive to manipulate. This result is supported by the findings of initial model, where Beneish found no evidence of relation between manipulators and Sgae_I as well as Lev_I. The possible explanation to this could be debt covenants might not be enough for firm as an incentive to manipulate due to higher cost of manipulation.

The result of Sgae_I is similar to the univariate analysis that suggests no noticeable difference between manipulators and control firms concerning their selling, general and administrative expenses index. Similar results are reported by Dikmen and Küçükkocaoğlu (2010) who reported that since these expenses are variable and depend upon sale. There must be a constant correlation between the sale and these expenses. Any disproportionate change in these expenses would signal manipulation.

Model 2 reports the result with the addition of industry dummies. 10 industry dummies are included in the analysis, thus excluding textile and the related sector as a control sector to avoid the dummy trap. No remarkable change is noticed in the variable or their level of significance. Pseudo R^2 in model 2 is comparatively higher, showing an increase in the predictive power of the model with the addition of industry dummies. *Model 3* captures the effect of control variables and controls for industry-effect. The result shows that manipulator firms are significantly larger than the control firms ($p<0.01$). The coefficient of AGE is also positive and significant ($p<0.05$). The similar characteristics of manipulator firms are reported in other empirical researches (Dechow et al., 2011). Notwithstanding, the addition of control variables does not affect the relationship and significance level of other independent variables. Pseudo R^2 is also the highest for this model, thus indicating substantial precedence in the explanatory power of this model comparing to others. The results of other variables added in *model 4* suggest that Inven_ovsst has no significant relation with firm's propensity to manipulate. The coefficient is negative and insignificant ($p>.10$). Results are similar to the univariate results, suggesting no noticeable difference between manipulator and control sample firms. Operating profit margin, captured by OI/Sale has a positive and significant result ($p<0.05$). Consistently, manipulating firms have higher profit margins than non-manipulators, most probably by factiously adding revenue without a subsequent addition in expenses. Controlling for industry effect in model 5 brings no change in the coefficients of variables and their significance except IO/Sale. Overall, the model has improved in term of its Pseudo R^2 and classification accuracy.

Concluding Remarks

The above section presents the first stage of multivariate analysis to test the proposed hypothesis 2 (*H2: M-Score variables have positive relation with firm's propensity to manipulate*) and its sub-hypotheses. In this section, a probit model is estimated to test how these variables affect the firm's propensity to manipulate. The dependent variable, M, is a dichotomous variable representing 1 for the manipulators and zero for the control firms. In order to check the robustness of the estimates, various models are estimated using a) only M-Score variables, b) incorporating other variables and c) including control variables and industry dummies. The results show that Sgr_I, Dsr_I, Dep_I, Grm_I and TATA show significant and positive relation with the dependent variable M. The remaining indices Aqu_I, Sgae_I and Lev_I do not give a significant relation with the dependent variable. Hence, overall five out of eight indices showed a significant relation with the firm's propensity to manipulate. The result of Beneish (1999) initial analysis produced similar results. However, the three insignificant variables in the analysis were Dep_I, Sgae_I and Lev_I. He carried out the same analysis using 100 random estimation samples and results showed small variation (Beneish, 1999a; Beneish et al., 2012).*In terms of sub-hypotheses, results supported H2b, H2c, H2d, H2f and H2h (significant and positive relation in case of* Sgr_I, Dsr_I, Dep_I, Grm_I and TATA respectively*). Contrarily, we the results didn't support sub-hypotheses H2a, H2e and H2g (insignificant* Aqu_I, Sgae_I and Lev_I*).* Summing up, the results reported in the Table 4.5supported a partial acceptance of H2.

4.4.2. Estimation of Bivariate Probit

Table 4.7 reports the results of the bivariate probit model where we estimate the factors affecting the firm's propensity to manipulate, with conditional probability of detection of manipulation and factors that affect the detection of manipulation simultaneously. The first dependent variable is $M_{i,}$ a binary variable representing 1 for manipulators and zero for control. The second dependent variable D_i, represents the conditional probability of detection of manipulation; is a binary variable equals to 1 when a firm commits the fraud and gets caught and zero for otherwise.

The first two columns represent the factors determining the firm's propensity to commit fraud. These eight factors are same indices that are previously used in M-Score analysis of manipulators and control sample firms. The direction of the relation of indices are in accordance with the empirical findings in the research field (Beneish, 1999b; Maccarthy, 2017; Repousis, 2016) except Lev_I which has a negative coefficient with firm's propensity to manipulate ($p>0.1$). Sgae_I, was insignificant in simple probit M-Score analysis, represents a significant positive relation with M_i ($p<0.05$). All other indices have depicted similar results as of simple probit estimation.

Growth in M_i equation, represented by Sgr_I, has a significant positive association with firms' propensity to manipulate (coefficient=0.95, $p<0.01$). Likewise, Growth has a positive and significant association with the detection of fraud in equation D_i ($p<0.05$). It suggests that high growth firms have higher incentive to manipulate, and it also affects the detection of manipulation positively. Growing companies, as suggested by ACFE, are not necessarily manipulators, but they exhibit with a higher risk of manipulation by regulators and other monitoring agencies. Hence, high growth firms have a higher potential of being caught if they commit any fraudulent act (ACFE, 2016; Qiu, 2009). Accruals have positive effects on both M_i and D_i. Higher accruals show a higher probability of manipulation since it shows that the accounting profit of the firm are not backed by cash flows (Beneish et al., 2012). The result shows that accruals, proxied by WC_Accr, have significant and positive relation ($p<0.1$) with detection of manipulation. This result contradicts to the justification provided by Dechow et al. (2011) that higher working capital accruals are signs of overinvestment by managers, thus halting the reliability of detection of manipulation. It would cause hindrance to prove the manipulation by regulators. Inven/Sale has a negative and significant coefficient with D_i ($p<0.01$).

Table 4.7: ***Bivariate Probit Model for Manipulation (Fraud) with Conditional Probability of Detection of Manipulation***

Factors determining Fraud/Manipulation	*Model 1*				*Model 2*			
	Mi		*Di*		*Mi*		*Di*	
Aqu_I	0.5880				0.2409			
	(0.6424)				(0.4070)			
Sgr_I	0.9542***	0.9542***			1.0015***	1.0015***		
	(0.2050)	(0.2050)			(0.2274)	(0.2274)		
Dsr_I	0.6088***	0.6088***			0.6847***	0.6847***		
	(0.1128)	(0.1128)			(0.1381)	(0.1381)		
Dep_I	0.5652***	0.5652***			0.5135***	0.5135***		
	(0.2016)	(0.2016)			(0.1501)	(0.1501)		
Sgae_I	0.1782**	0.1782**			-0.0437			
	(0.0877)	(0.0877)			(0.0650)			
Grm_I	0.1863***	0.1863***			0.3956***	0.3956***		
	(0.0708)	(0.0708)			(0.0793)	(0.0793)		
Lev_I	-0.1273				-0.2618*	-0.2618*		
	(0.2211)				(0.1529)	(0.1529)		
TATA	3.0400***	3.0400***			3.3507***	3.3507***		
	(0.8221)	(0.8221)			(0.7483)	(0.7483)		
Other Variables								
Inven_ovsst					2.48E-07***	2.48E-07***		
					(7.20E-08)	(7.20E-08)		
OI/Sale					5.47E-06***	5.47E-06***		
					(2.42E-06)	(2.42E-06)		
The factor for Detection of Manipulation								
INV			-431.65				-586.26*	-586.26*
			(560.83)				(317.76)	(317.76)
CROA			-0045				-0.0041	
			(0.0047)				(0.0030)	
Growth			2.28E-08**	2.28E-08**			1.57E-08*	1.57E-08*
			(1.07E-08)	(1.07E-08)			(9.29E-09)	(9.29E-09)
WC_Accr			9.06E-08*	9.06E-08*			6.73E-08**	6.73E-08**
			(4.91E-08)	(4.91E-08)			3.25E-08	(93.37E-08)
Inven/Sale			-0.3165***	-0.3165***			-0.2855***	-0.2855***
			(0.1299)	(0.1299)			0.1057	0.1057
Constant	-3.867***		-0.3065***		-2.973***		-0.2695***	
	(0.8410)		(0.0673)		(0.6661)		(0.0641)	
ρ (p-value)	77.97***				63.57***			
Log pseudo-likelihood	-532.07				-450.65			
Wald χ^2 (d.f.)	53.02 ***(13)				49.80***(15)			
No. of obs.	592				590			

Note: The table reports factors affecting the probability of manipulation and the conditional probability of detection of manipulation. Robust standard errors reported in parentheses. ***, ** *and* * *represents significance level at p-value 0.01. 0.05 and 0.1, respectively. The definition and proxies of variables discussed in chapter 3. All the variables are winsorized at 1% and 99% to remove extreme values. Source: author's estimation.*

It suggests that a higher Inven/Sale ratio lowers the chance of detection of fraud and vice versa. The coefficients of investment intensity INV and unexpected performance shock CROA in *model 1* is negative, as suggested by related empirical literature (Chen et al., 2006; Qiu, 2009), however the insignificant *p*-value would lead us to conclude that both of these determinants do not affect the probability of detection of manipulation. Rho (ρ) captures the correlation between disturbances of two equations. If the value of ρ is not significantly different from zero, it means that simultaneous probit model will not work out, and two individual probit models should be replied (Feinstein, 1990). Results of ρ is *77.97 with* $p<0.01$. The result suggests that simultaneous probit system of equation is *a good fit*. Value of Wald χ^2 is also significant with $p<0.01$.

In *Model 2*, we estimate the same bivariate probit with additional determinants for testing the firm's incentive to manipulate, conditionally in association with the detection of manipulation. All the indices of M-Score for firm's propensity to manipulate exhibit no remarkable change in term of the direction of relation and p-value. Sgae_I, on the other hands, shows an insignificant and negative relation with dependent variable M_i. Contrary to the findings of Beneish who found no evidence of a relation between Lev_I and manipulation (Talab et al., 2017), this model reports a significant and negative relation between Lev_I and M_i ($p<0.1$). The results corroborate to the findings of Dichow et al. (2011), who reported that misstating firms are concerned about raising finances in the years before manipulation. Hence, leverage, might not be motivating factors for the firms to misstate. Inv_ovsst, the ratio of change in inventory to beginning year assets, is significantly higher for manipulators than the control firm ($p<0.01$). Similar evidence is provided by Rosner (2003), who demonstrated a higher tendency of manipulator sample firms to overstate inventory than the control firms (Rosner, 2003).

OI/Sale is also a significant determinant of the firm's propensity to manipulate ($p<0.01$). The findings contradict to the results of Beneish, who identified manipulators as characterized by low-profit margins and supported by the argument that deteriorating profit margins can motivate the firm to manipulate (Beneish, 1997).

Investment intensity, *INV* has a negative relation with the detection of manipulation D_i with the estimated (significant) coefficient of INV is *-1713.1*, suggesting that a one unit increase in investment intensity would cause a 1713 point decrease in the probability of detection of manipulation. This result is supporting the findings of Wang (2004), who reported that higher investment would create difficulty for the fraud detection due to the associated difficulty in predicting correct cash flow estimates (Wang, 2004). Correspondingly, Wang (2011) also proved that new investment by managers could create noise, thus limiting the abilities of regulators to identify and correctly predict cash flows. The other factors affecting the firm's probability of detection of manipulation remains the same in term of their coefficient and p-value. For instance, return volatility, CROA is negative and insignificant (p>0.1). Other factors affecting probability of detection of manipulation, i.e., Growth, WC_Accr, Inven/Sale show no change in predicted coefficient in terms of signs and significance. At the bottom of the table, significant rho value shows that the model is a good fit. Similarly, the value of Wald χ^2 is significant at p>0.01. In other words, adding the predictors resulted in a statistically significant improvement in model fit.

Table 4.8 presents the initial model with controlling the effect of size *(SIZ)*, age *(AGE)* and industry *(Industry dummies)*. The univariate analysis and simple probit estimation of M-Score also showed that manipulators and control are different in term of their size and age. The industry distribution of manipulators also confirmed that propensity to manipulate and detection of manipulation varied across industries. The reported cases in some industries, e.g., cases of manipulation in textile and allied, are highest in numbers as compared to the service sector. Similarly, industries tend to vary in terms of detection risk of fraud. Many studies confirmed that the occurrence of financial statement manipulation is more prominent in specific industries (Beasley, Carcello, Hermanson, & Lapides, 2000). Presence of higher concentration of fraud in technology and related industries (Dechow et al., 1996), manufacturing (Beneish, 1997), and finance and insurance (Dechow et al., 1996). Therefore, AGE, SIZ and Industry Dummy are predicted to capture the effect of size, age and industry variation on bivariate *probit* estimation. SIZ has a significant coefficient, both with the propensity of manipulation and detection of manipulation. The positive coefficient of size (*p<0.01*) in the first two columns show that manipulators are significantly larger firms than their control counterparts. Size gives a significant positive relation with the probability of detection of manipulation. It is in consistent with the argument that larger firms face tighter scrutiny, thus leading to a higher probability of detection if they commit any fraud (Dechow et al., 2011). Throckmorton, Mayew, Venkatachalam, and Collins (2015) noted the similar relation between firm size and corporate misreporting. They reported that large firms with

Table 4.8: ***Bivariate Probit Model for Propensity of Manipulation and Detection (with Control variables)***

	Model 1				*Model 2*			
	Mi		*Di*		M_i		D_i	
Aqu_I	0.5570				0.8316			
	(0.6622)				(-0.7661)			
Sgr_I	0.8931***	0.8931***			1.0153***	1.0153***		
	(0. 2128)	(0. 2128)			(-0.2164)	(-0.2164)		
Dsr_I	0.6252***	0.6252***			0.6680***	0.6680***		
	(0.1153)	(0.1153)			(-0.111)	(-0.111)		
Dep_I	0.6200***	0.6200***			0.5983***	0.5983***		
	(0.1251)	(0.1251)			(-0.2481)	(-0.2481)		
Sgae_I	0.1659*	0.1659*			0.2527***	0.2527***		
	(0.0885)	(0.0885)			(0.0975)	(0.0975)		
Grm_I	0.1796***	0.1796***			0.1884***	0.1884***		
	(0.0712)	(0.0712)			(-0.0798)	(-0.0798)		
Lev_I	-0.1210				-0.2009			
	(0.2337)				(-0.2625)			
Tata	2.8302***	2.8302***			2.5124***	2.5124***		
	(0.8546)	(0.8546)			(-0.8786)	(-0.8786)		
Inven_ovsst	1.36e-07	1.36e-07			7.04-08			
	(1.25e-07)	(1.25e-07)			(-1.40E-07)			
OI/Sale	0.000012*	0.000012*			0.00001			
	(7.15e-06)	(7.15e-06)			(7.15E-06)			
INV			-898.39*	-898.39*			-1713.1***	-1713.1***
			(525.26)	(525.26)			(520.41)	(520.41)
CROA			-0.0062*	-0.0062*			-0.0075	
			(0.0033)	(0.0033)			(0.0063)	
Growth			2.05e-08**	2.05e-08**			9.98e-09	
			(9.77e-09)	(9.77e-09)			(1.32e-08)	
WC_Accr			5.60e-08				9.43e-08	
			(3.66e-08)				(5.83e-08)	
Inven/Sale			-0.3129	-0.3129***			-0.3509**	-0.3509**
			(0.12743)	(0.12743)			(0.1827)	(0.1827)
Siz	0.2540***	0.2540***	0.31537***	0.31537***	0.2545***		0.3048***	0.3048***
	(0.0437)	(0.0437)	(0.03490)	(0.03490)	(0.0497)		(0.0393)	(0.0393)
Age	0.0893		-0.0124		-0.0037		-0.0013	
	(0.1658)				(0.0074)		(0.0059)	
Industry Dummy			*NO*				*YES*	
Constant	-7.2928***		-4.5896***		-8.8509***		-5.5774***	
	(1.1658)		(0.6333)		(1.3348)		(0.61788)	
ρ (p-value)			73.44***				57.094***	
Log pseudo–likelihood			-482.65				-398.58	
Wald χ^2 (df)			142.78*** (19)				247.64*** (39)	
No. of obs.			590				583	

Note: *This table reports the result of bivariate probit regression by incorporating control variables. Robust standard errors reported in parentheses.* ***, ** *and* * *represents significance level at p-value 0.01. 0.05 and 0.1, respectively. The definition and proxies of variables discussed in chapter 3. All the variables are winsorized at 1% and 99% to remove extreme values. Source: author's estimation*

poorer financial prospects tend to manipulate earnings. The findings, however, contradict to the results reported by (Beasley, 1996), who found a negative relation between size and firms engaged in overstatement. Another control variable, Age, represents no significant relation with either M_i or D_i. Moreover, no significant change is noticed in other predictors of manipulation and detection of manipulation after incorporating control variables. The estimates, such as rho value and Wald χ^2 confirm the *fitness* of the predicted model.

Concluding Remarks

Table 4.7and Table 4.**8** report the results of bivariate probit models, capturing the predictors of firm's propensity to manipulate and conditional probability of detection of manipulation. Bivariate probit estimation is carried out in order to check the estimate of manipulation with the conditional probability of the detection of the manipulation (Qiu, 2009; Wang, 2004). Hypotheses 3 and 4 (*H3, H4*) are tested used a simultaneous analysis of the explanatory variables with dependent variable M_i and D_i. The analyses show how the estimates of profitability and growth affect the dependent variables in a simultaneous setting. From *Table 4.7*, it is inferred that growth, measured by Sgr_I is positively related to firm's propensity to manipulate. For the second half of the equation, growth is proxied by change in sale volume over time. The coefficients of growth are positive and significant for *Mi* and *Di* (Both *H3a* and *H3b* are supported.). The results suggest that high growth firms are at higher risk and have greater incentive to manipulate their earnings and represent high risk of detection (Beneish, 1999a). Growth, per se, is not negative, but firms with higher growth can capture the regulators attention therefore the risk of their being caught increases (Qiu, 2009). *Therefore we can accept H3 (Growth of the firm is positively related to the firm's propensity to manipulate and probability of detection of manipulation).*

Beneish (1999) reported that manipulating firms have deteriorating profitability margins, which gives them incentive to manipulate. Wang (2004), however, reported that this measure of profitability is ex-ante (Wang, 2004). The results in the Table 4.7 and 4.8 confirm the deteriorating gross margin (positive Grm_I suggests a decreasing gross profit margin over time) for the firm's propensity to manipulate M_i (*H4a* is supported). The operating margin, on the other hand, gave a partial positive relation with M_i. The ex-post measure of unexpected performance shock, measured by CROA gave a negative and significant result with probability of detection of manipulation D_i in Table 4.8 only (partial support for *H4b*). *Hence the overall results lead us to the partial acceptance of proposed H4 (Profitability of the firm is negatively related to the firm's propensity to manipulate and probability of detection of manipulation).*

4.4.3. Robustness Check

The theoretical and empirical literature on fraud and manipulation has evidenced that certain factors affect the probability of detection of manipulation and the firm's decision to manipulate (Li, 2013). So a simple probit model, that assumes perfect detection, does not differentiate the incidence of manipulation and probability of detection of manipulation. It may lead to a biased estimate and affect the outcome of the analysis. Subsequently, in order to check the robustness of the results, this study conducted additional analysis. This includes:

a) testing impact of investment intensity (see Table 4.9) on both fraud manipulation and detection simultaneously (Wang, 2011) and
b) comparing the results of simple estimation and bivariate probit model to understand the differences in predicted coefficients (Table 4.10).

Firstly, supporting probability detection of manipulation a bivariate model used to capture partial observability; all the determinants of manipulation represent no remarkable change from the previously discussed estimation results. The sign and predicted coefficients and their significance level correspond to reported findings discussed above. The exciting result is depicted by INV, which shows a positive and significant result ($p<0.01$) with the firm's propensity to manipulate. In contrast, INV shows a negative and highly significant relationship with the probability of detection of manipulation ($p<0.01$). The result corroborates to the findings and assumptions of Wang (2011), who reported that investment intensity is a significant determinant of manipulation commission and detection, but in the opposite direction. New investment can generate cash flows that can cause noise, thus limiting the ability of regulators to detect any fraud or manipulation.

Wang (2011) gave justification for the findings by reporting that a lower probability of detection of fraud increases the firm's incentive to commit fraud (Wang, 2011; Wang, 2004). Hence, the reported results, are supported by empirical and theoretical findings in corporate misconduct research (Qiu, 2009). The significant rho value and Wald χ^2 prove the fitness of the model.

Table 4.9: ***Investment, Propensity of Manipulation and Detection***

	Mi		*Di*	
Aqu_I	0.8371			
	(0.7567)			
Sgr_I	1.0300***	1.0300***		
	(0.2160)	(0.2160)		
Dsr_I	0.6710***	0.6710***		
	(0.1110)	(0.1110)		
Dep_I	0.6322***	0.6322***		
	(0.2441)	(0.2441)		
Sgae_I	0.2706***	0.2706***		
	(0.0970)	(0.0970)		
Grm_I	0.1941***	0.1941***		
	(0.0799)	(0.0799)		
Lev_I	-0.1841			
	(0.2606)			
Tata	2.601***	2.601***		
	(0.8768)	(0.8768)		
Inven_ovsst	9.76e-08			
	(1.42e-07)			
OI/Sale	.00001			
	(7.41e-06)			
INV	20647.9***	20647.9***	-1473.63***	-1473.63***
	(7309.6)	(7309.6)	(583.71)	(583.71)
CROA			-0.00815	
			(0.0063)	
Growth			1.08e-08	
			(1.32e-08)	
WC_Accr			9.35e-08	
			(5.82e-08)	
Inven/Sale			-0.3502**	-0.3502**
			(0.1843)	(0.1843)
Siz	0.2517***	0.2517***	0.3022***	0.3022***
	(0.0495)	(0.0495)	(0.0392)	(0.0392)
Age	-0.0046		-0.0014	
	(0.0075)		(0.0059)	
Indus Dummy		*YES*		
Constant	-8.9194***		-5.5368***	
	(1.2928)		(0.6158)	
ρ (p-value)		56.96***		
Log pseudo-likelihood		-396.04		
Wald χ^2 (df)		260.67*** (40)		
No. of obs.		590		

Notes: This table reports the result of bivariate probit by including the effect of overinvestment on firm's propensity to manipulate M_i and probability of detection of manipulation D_i. Moreover, control variables and industry dummy have also been incorporated. All the variables are winsorized at 1% and 99% to remove extreme values. The operational definition of variables has discussed in chapter 3. Robust standard errors are reported in parentheses. ***,** and * represent level of significance for p values 1%, 5% and 10% respectively. Source: author's estimations.

4.4.3.1 Comparing the Results of Simple Estimation and Bivariate Probit Model

As part of robustness check, a simple probit (discrete choice) model is estimated, which equates the probability of detection of manipulation with the commission of manipulation. Since the probit model doesn't distinguish the *probability of manipulation commission and detection of manipulation,* all the coefficient estimates could be assumed as explanatory variables affecting the firm's propensity to manipulate or probability of detection of manipulation or both (Perols, 2008). Table 4.10 compares the estimates of simple probit model with marginal effects of probability, captured by bivariate probit estimation. As reported by Li (2013), the discrete choice model captures the effects of the explanatory variable on latent variable Y, while marginal effects represent the effect of the explanatory variable on the probability of Y=1.

The reported results show that straight probit model has the same coefficients of all indices of M-Score and represents consistent effects in sign and significance across bivariate estimation. However, the magnitudes of the coefficients are different as evidenced from marginal effects of bivariate probit estimate of the probability of manipulation. For the predictors of detection of manipulation, INV has a higher, positive and significant coefficient in straight probit model (roughly 1.3 times marginal coefficient of INV in the probability of manipulation commission M_i). However, it is unclear that whether the manipulator firms have higher investment intensity and whether the market directs more scrutiny to these firms which results in detection of these firms (Das, Shroff, & Zhang, 2012). Bivariate model, on the other hand, reports an opposing effect of INV on manipulation commission and detection of manipulation (Table 4.9), this effect cannot be captured through a single probit based estimation (Wang et al., 2010). The coefficients of GROWTH and WC_Accr have a negative and significant effect as shown in a straight probit model, whereas it represents no effect in the bivariate estimation of the probability of detection. Overall estimation shows that the bivariate probit model, capturing probability, is different from straight probit estimation (Li, 2013). The estimates of model fit are presented at the bottom of Table 4.10. The estimation results confirm the high correlation between the two probabilities as indicated by bivariate probit. This is depicted by the Wald test of the correlation coefficient of the error terms (rho), which indicates that we cannot reject the null hypothesis that the unobserved factors affecting the probability of manipulation commission and the probability detection of manipulation are uncorrelated. Rho is therefore significantly different from zero ($\rho \neq 0$). As such, the test

Table 4.10: *Comparison of Simple Probit with Bivariate Probit Estimation*

	Probit		*Bivariate Probit*			
	Mi		M_i		D_i	
Aqu_I	1.4817		0.8371			
	(0.9134)		(0.7567)			
Sgr_I	1.9151***	1.9151***	1.0300***	1.0300***		
	(0.2752)	(0.2752)	(0.2160)	(0.2160)		
Dsr_I	1.0826***	1.0826***	0.6710***	0.6710***		
	(0.1481)	(0.1481)	(0.1110)	(0.1110)		
Dep_I	0.7884***	0.7884***	0.6322***	0.6322***		
	(0.3026)	(0.3026)	(0.2441)	(0.2441)		
Sgae_I	0.2867**	0.2867**	0.2706***	0.2706***		
	(0.1399)	(0.1399)	(0.0970)	(0.0970)		
Grm_I	0.4831***	0.4831***	0.1941***	0.1941***		
	(0.1037)	(0.1037)	(0.0799)	(0.0799)		
Lev_I	-0.2049		-0.1841			
	(0.3324)		(0.2606)			
Tata	5.3196***	5.3196***	2.601***	2.601***		
	(1.2035)	(1.2035)	(0.8768)	(0.8768)		
Inven_ovsst	7.02e-08		9.76e-08			
	(1.96e-07)		(1.42e-07)			
OI/Sale	0.00001*	0.00001*	.00001			
	(7.65e-06)	(7.65e-06)	(7.41e-06)			
INV	25137.3***	25137.3***	20647.9***	20647.9***	-1473.63***	-1473.63***
	(10214.02)	(10214.02)	(7309.6)	(7309.6)	(583.71)	(583.71)
CROA	0.0116				-0.00815	
	(0.0074)				(0.0063)	
Growth	-4.93e-08**	-4.93e-08**			1.08e-08	
	(2.45e-08)	(2.45e-08)			(1.32e-08)	
WC_Accr	-1.78e-07**	-1.78e-07**			9.35e-08	
	(8.45e-08)	(8.45e-08)			(5.82e-08)	
Inven/Sale	-0.2604				-0.3502**	-0.3502**
	(0.2508)				(0.1843)	(0.1843)
Siz	0.2281***	0.2281***	0.2517***	0.2517***	0.3022***	0.3022***
	(0.4961)	(0.4961)	(0.0495)	(0.0495)	(0.0392)	(0.0392)
Age	0.1811		-0.0046		-0.0014	
	(0.1888)		(0.0075)		(0.0059)	
Dummy	YES		*YES*			
Constant	-11.41***		-8.9194***		-5.5368***	
	(1.6495)		(1.2928)		(0.6158)	
ρ (p-value)			56.96***			
Log pseudo-likelihood	*-160.71*		-396.04			
Wald χ^2 (*d. f.*)	*179.97***(27)*		260.67*** (40)			
Pseudo R^2	*0.5385*					
No. of observations	583					

Notes: This table reports the result of simple probit model and compares it with the estimates of bivariate probit. All the variables are winsorized at 1% and 99% to remove extreme values. The operational definition of variables has discussed in chapter 3. Robust standard errors reported in parentheses. ***,** and * represent level of significance for p values 1%, 5% and 10% respectively. Source: author's estimations

indicates that the bivariate probit model is a suitable procedure for modelling these two probabilities using this particular data set.

Concluding Remarks

In this section, robustness of the estimated model is analyzed by incorporating investment intensity in both *Mi* and *Di* equations. The results of bivariate probit model, as shown in Table 4.9, appear to support the proposed hypothesis *H5*. A higher level of investment by the manipulators firms is done in order to deceive the external monitoring agencies and regulators. This limits the efficiency of prediction of true cash flow estimation of the firms. As a consequence, the probability of detection of the manipulation is lowered. The result supported similar notion; a significant and positive coefficient of INV with Mi and a significant and negative coefficient of INV with Di confirms the proposed hypothesis. Therefore, we can conclude that both sub-hypotheses i.e., *H5a* and *H5b* are fully supported.

Hence, hypothesis 5 is accepted (Investment intensity has a positive effect of the firm's propensity to manipulate and negative effect on the probability of detection of manipulation).

Table 4.10 compares estimates of bivariate probit model with straight probit model. As discussed earlier, simple probit model assumes perfect detection. It equates probability of detected fraud to the probability of manipulation, thus could lead us to inconsistent estimates (Zhang, 2018).

5. Conclusions, Limitations and Implications

The goal of this chapter is to discuss and conclude the result of empirical testing reported in the previous chapter. The results are summarized on the basis of proposed hypotheses and analyses types. The next section includes the implications of the results for various stakeholders. Finally, the limitations of this study and proposed future directions are discussed.

5.1 Findings of the Research

The primary goal of this study is to concentrate on financial reporting fraud, which is one of the significant concerns affecting the quality of financial reporting. These types of frauds involve a deliberate intent to fabricate the facts or omit the material information purposefully to deceit the investors and other stakeholders. The magnitude of the harm caused by financial statement frauds makes them one of the most hazardous types of corporate unethical behaviours (Rezaee, 2002). This study extends this discussion by highlighting partial observability of frauds. An extensive literature review is conducted to ascertain the prevalent research gap by encompassing both theoretical and empirical studies of fraud-related research. Moreover, this study comprises the empirical testing of models using sophisticated statistical analyses.

A rigorous effort is directed to identify the firms alleged of manipulation by the Securities and Exchange Commission of Pakistan (SECP). The identity of companies is kept anonymous since revealing the names of firms is out of the scope of this study. The data for alleged firms is collected using annuals reports and Balance Sheet Analysis (A database published by State Bank of Pakistan). For analysis, a matched sample of firms, called control firms, is collected based on the industry classification, size and age with test firms. This study compliments the fraud related empirical models developed by Beneish (1999) and Wang (2004, 2011, 2013). These models were initially tested on firms based in US. The main novelty of this study is to test and compare the models in a developing economy context and provide empirical evidence in the case of Pakistan. Financial reporting fraud seems to be common in Pakistan[6] but unlikely to be caught by regulators, fraud examiners or by external auditors. The proposed methodology can be easily used by public auditors and regulatory agencies in order to assess the likelihood of accounting fraud, in combination with other

[6] Transparency International report on Integrity Risks for International Businesses in Pakistan (2018-19) mentions fraud as a major hurdle to business growth in Pakistan. Experts consulted for this survey pointed to the common practice among Pakistani SMEs of maintaining two sets of books of financial information and indulge in other illicit accounting practices to hide financial transactions from tax inspectors and international partners (Transparency International, 2018).

investigative efforts to better design and implement detection mechanism for illicit accounting practices.

5.1.1. Univariate Analysis

For analysis, this study employed a combination of univariate and multivariate analyses techniques to validate the empirical confirmation of proposed hypotheses. Univariate analysis is conducted to identify the general characteristics of manipulators and control firms by incorporating descriptive statistics (mean value, standard deviation, etc.), *T-test*, Wilcoxon Z test and *Median test*. The overall characteristics of manipulators show that they are high growth firms. They have deteriorating fundamentals, especially gross margin index. The difference between age and size of manipulators and control firms is insignificant. The average age of manipulators is marginally higher than control firms. The comparison of M-Score indices of manipulators and control firms lead us to conclude that both groups are significantly different from each other based on their asset quality index, sales growth index, depreciation index and gross margin index. The remaining indices depict no significant difference between the groups. Hence, we can partially accept H1 hypothesis. *Manipulators and control firms are significantly different from each other based on M-Score variables).*

5.1.2. M-Score Analysis

The multivariate analysis comprises of three stages: 1) in the initial stage, the M-Score baseline model is analyzed by comparing the sample of manipulators and control firms. 2) In the second stage of multivariate analysis, a bivariate probit model is tested, capturing the firms' propensity to manipulate and a conditional probability of detection of manipulation in a simultaneous-setting. 3) In the third stage, the results of the bivariate probit model are compared with simple probit regression to validate the suitability of the model.

In the first stage, M-Score analysis is conducted in order to test the following hypothesis (H2); *'M-Score variables have a positive relationship with the firm's propensity to manipulate'*. In this model, the dependent variable is represented by letter M, which is a binary variable representing 1 for the group of manipulators and zero for control firms, matched to manipulators based on size, age and industry classification. The result of M-Score analysis shows that the coefficient of assets quality index, *asset quality index* though positive, gives insignificant relation. Sales growth index gives a positive and significant relationship with the firms' propensity to manipulate. It is consistent with the fact that growing companies have a higher likelihood of manipulation and fraud.

Similarly, the result of *days' sales in receivable index* suggests that manipulator firms revise their receivable upward disproportionately, and have a higher probability of sales revenue manipulation (Beneish, 1999). Consistently, a significant and positive coefficient of *depreciation index* elucidates that manipulating firms have higher depreciation that is achieved by either changing method or increasing assets' useful life. Results of *gross margin index* depict worsening performance of manipulators. Consequently, they have greater incentive to manipulate. The positive and significant relationship of accrual coefficient confirms that manipulators have less cash profit than their accounting profit figures; accounting profits figures are not supported by the magnitude of the cash profit.

Table 5.1: Summary of Model Specification

Variables	**Applied Methodology**			**Results**
	Probit Model	***Bivariate Probit***		
	M	M_i	D_i	
Asset Quality Index	+			*H2a* is not supported
Sales Growth Index	+	+		*H2b* and H3a are supported
Days' Sales in Receivables Index	+			*H2c* is supported
Depreciation Index	+			*H2d* is supported
Selling, General And Administrative Index	+			*H2e* is not supported
Profitability (Gross Margin Index)	+	+		*H2f* and *H4a* are supported
Leverage Index	+			*H2g* is not supported
Total Accruals To Total Assets	+			*H2h* is supported
Investment Intensity		+	-	*H5a* and *H5b* are supported
(Profitability) Unexpected Performance Shock			-	*H4b* is supported
Growth		+	+	*H3a* and *H3b* are supported
Working Capital Accruals			+	-
Change in Inventory to Change in Sale			+	-
Control Variables Size, Age. Industry				-

Source: Author's construction (2019)

The remaining indices, selling, general and administrative expenses index and leverage index show no significant relation with firm's propensity to manipulate. The results support a partial acceptance of hypothesis H2. *M-Score variables have a positive relationship with the firm's propensity to manipulate*.

5.1.3. Bivariate Probit Analysis

This study incorporated *the bivariate probit model*; a model that can generate testable implications for the determinants of cross-sectional differences between firms' propensities to manipulate and detection of manipulation. The literature on financial fraud and manipulation predicts that fraudulent firms tend to have higher growth prospects and experience adverse profitability shocks. The risk of litigation is clustered in certain types of industries during a specific period. The theory on corporate manipulation also suggests that firm's that are fraudulent tend to overinvest. This overinvestment supports them to betray the investors and analysts as it can reduce the certainty of future cash flow prediction. Consequently, the likelihood of detection of manipulation is reduced.

In the second stage of multivariate analysis, the determinants of the firm's probability to manipulate and the probability of detection of manipulation are investigated using the sample of firms alleged of manipulation by SECP and a matching sample of control firms. The econometric model is used to control the probability of undetected manipulation and disentangle the effect of a factor on the firm's probability to manipulate and the likelihood of detection of manipulation. The result of the analysis indicates that estimates of growth and profitability significantly affect the firms' propensity to manipulate. Growth, measured by sales growth index is positively related to the firms' propensity to manipulate. For the second half of the equation, growth is proxied by a change in sales volume over time. The coefficients of growth are positive and significant for M_i and D_i. Consequently, the results lead to the overall acceptance of third hypothesis H3. *Growth of the firm is positively related to the firm's propensity to manipulate and the probability of detection of manipulation*.

The other indices showing a significant and positive relationship with the firm's propensity to manipulate include *days' sales in receivable index, depreciation index, selling, general and administrative expenses* index and *total accrual to total assets*. The results show that larger firms in Pakistan have higher propensity to manipulate. Financial reporting fraud is more likely in the larger firms having, higher sales growth and assets.

The result of profitability in the first equation, M_i, gives mixed results. The manipulating firms were hypothesized to have deteriorating performance. The other measure of performance, on the other hand, gives a partial positive relation with the firms' propensity to manipulate. The ex-post measure of unexpected performance shock, measured by *change in return on assets*, gave a negative and significant result with the probability of detection of manipulation Di. Hence the results lead us to the partial acceptance of proposed H4. *Profitability of the firm is negatively related to the firm's propensity to manipulate and the probability of detection of manipulation*.

Investment intensity also affects the firm's propensity to manipulate and the likelihood of the detection of manipulation. The results indicate that a higher level of ex-ante investment by the manipulators is done in order to deceive the external monitoring agencies and regulators. It limits the efficiency of the prediction of accurate cash flow estimation of the firms. As a consequence, the ex-post probability of detection of the manipulation is lowered. *Hence, hypothesis 5 is accepted (Investment intensity has a positive effect of the firm's propensity to manipulate and negative effect on the probability of detection of manipulation).*

Table 5.2: Summary of the Empirical Analyses

Sr. No.	Hypotheses	Expected Sign			Statistical Support
		M	*Mi*	*Di*	
H1:	Manipulators and control firms are different from each other based on M-Score variables				Partially supported
H2:	M-Score variables have a positive relationship with the firm's propensity to manipulate.	+			Partially supported
H3:	Sales growth of the firm is positively related to the firm's propensity to manipulate and the probability of detection of manipulation		+	+	Supported
H4:	The profitability of the firm is negatively related to the firm's propensity to manipulate and the probability of detection of manipulation		-	-	Partially supported
H5:	Investment intensity has a positive effect on the firm's propensity to manipulate and has a negative effect on the probability of detection of manipulation		+	-	Supported

Source: Author's construction (2019)

5.2 Implications

Financial frauds imposed a considerable burden on the financial markets. Shareholders of alleged firms may lose millions of dollars on the public announcement of corporate accounting irregularities. The bankruptcy of Enron put an unprecedented emphasis on the accounting profession and its role in the regulatory mechanism of the financial reporting process. In addition to the wealth loss faced by the investors, the issue of fraudulent financial reporting also contributes to an enormous welfare cost, especially when resources are misdirected from their most effective use (Beneish, Lee, & Nichols, 2012). These accounting manipulations and misrepresentation of facts place a surge in the eroding investor's confidence and integrity of capital markets. These accounting manipulations are followed by the number of regulatory reforms (often very costly) and structural changes in the regulations of firms and the markets. Enhanced diligence on the part of investors and auditors was observed for scrutiny of financial information (Chan, Chou, & Lin, 2016).

This study has vital implications, especially for the firms, policymakers and academicians. Corporate accounting frauds and manipulations have severe financial and non-financial consequences for the firms. Organizations, which try to prevent frauds and manipulations, usually do so by working on one of the essential elements of fraud triangle: opportunity (Morales et al., 2014). This study has shed light on various firms-related factors that can serve as potential opportunities for the managers and accountant to commit and conceal manipulation. These opportunities might serve as incentives and motivations for fraudulent acts. These opportunities can be eliminated by incorporating proper internal controls and then directing all the efforts to implement those control measures and ensuring strict adherence to them. Having an effective control environment is one of the most important steps that organizations can take to avoid manipulations and frauds. An appropriate control environment includes management's role and examples (ACFE, 2016). Numerous fraud incidences studied here usually involved SECP enforcement for employees’ fraud, which in turn was a learned behaviour from dishonest managerial practices. So, an appropriate tone at the top must be ensured to avoid the huge costs that the firms have to endure in the aftermath of frauds or other dishonest acts. Developing economies are characterized by week corporate governance practices and the monitoring mechanism of the firms (Ghafoor et al., 2018). One of the major implications for firms is to put all the energies to build an appropriate corporate governance and 'tone at the top'. Meanwhile, this tone at the top should be communicated well throughout the organization to maintain a 'zero tolerance' culture for manipulation and unethical behaviour. Such culture will help the firms to develop a well-designed control system that reduces the opportunities for the frauds and enhance the probability of quick detection of frauds.

The result of this study also suggests that manipulators tend to overinvest. While, the empirical and theoretical studies also suggest that investment has a spill-over effect between manipulators and other firms (Wang, 2013). The overinvestments made by manipulators tend to crowd out investment by non-manipulators firms. It has implications for the capital market in the form of a real loss of value, while this loss is borne not only by the manipulators but other firms too that have no intention to manipulate their earnings.

This study also offers implications for regulators and standard setters who are endeavouring to reinforce the monitoring oversight in the financial markets. The firm-specific factors highlighted in this study can help the regulators and standard setters to focus on these specific factors to curb the firm's fraud intention and accelerate the process of detection. The disentangling of fraud commission and detection addressed in this study can support the regulators to put augmented efforts to identify the undetected cases. Combating accounting fraud and manipulation requires regulatory initiatives, strict monitoring and control mechanisms by SECP, PSX and other regulators. The accounting and security market regulators can curb these frauds through legislation, enforcement actions and by taking severe actions against perpetrators.

This study also offers implications to the regulators in Pakistan. especially the methodology offered in this study will help to reduce measurement error, Type I and Type _II. The major hurdles for the regulators is budget deficiency as suggested by empirical researches, regulatory bodies consider only those cases which are too significant to ignore or which has already been exposed in some form. The offered methodology of the study is helps the regulators to access the information using financial statement data only, which they already has access to. This will help to minimize the chance of detection of undetected culprit (type II error).

This study also has implications for potential investors, shareholders and the general public at large, which are relying on the financial information published by companies to make investment decisions and evaluate the companies' prospects. The empirical results offered by this study question the reliability of financial information since firms are managing their earning for showing better-than-actual performance. The indices of Beneish M-Score also offered partial evidence that manipulators and non-manipulators firms are different from each other. Investors, therefore, should analyze the institutional settings of the firms, its past reputation, industry type and corporate governance mechanisms.

This study also has valuable implications for theorists and academicians. The results offer deep insight to segregate the phenomena of fraud commission and detection by questioning the existing literature based solely on the notion of perfect detection of fraud and manipulation (Poirier, 1980). Besides, this study offers greater insight into the researchers focusing on developing economies.

5.3 Limitations and Directions for Future Research

This study has several limitations, so enhanced care must be exercised before generalizing the results. First, this study considers only those forms of fraud and manipulation, which are affecting the integrity of financial information published by the firms. The other forms of corporate fraud and misconduct such as bribery, corruption, theft by employees and other deviant workplace behaviour are out of the scope of this study. Second, this study considers firm-level factors affecting the firm's incentive to manipulate and ex-post detection of fraud. There are several factors that were beyond the scope of this study, such as management style and corporate culture and 'tone at the top' that could have obvious effects on the firm's incentive to manipulate. Third, though due care was taken while choosing the manipulators and control sample firms, yet there are still margins of error since some of the firms included in the control sample might be an undiscovered manipulators. The difficulty in the process of detection process might be a result of budget deficiency of regulatory and monitoring bodies, i.e. SECP. Forth, while dealing with a troubled firm, the main challenge is to find published financial information, especially in the case of bankruptcy. It limits the size of the alleged firms chosen in the sample. Moreover, the element of unanimity is kept since disclosing the firms is out of the scope of this study. Manipulation and frauds have snowball effects, one leading to others. Though a due care is exercised in identifying year fraud was discovered, in many cases, the underlying issue is the detection of fraud when the effects of fraud are too significant to ignore.

This study identified gaps in the literature and has more significant future research potential. For instance, this study focused on the firm-related factors affecting the firm's propensity to manipulate. The firms do not operate in a vacuum. The macro-environment and institutional factors affect the firm's behaviour. Macro-sociological view of financial fraud incorporates broader economic, social and political theories, while micro view presents the interaction of the individual with corporate culture and environment (Holtfreter, 2005). Hence this study calls for further research to incorporate institutional factors affecting the firm's choice of manipulating financial information. Within firm-related factors affecting frauds, this study focused only on the financial incentive that can cause pressure on the firms for fraudulent behaviour. Future researches might incorporate the behavioural elements to grasp a better understanding of the diverse nature of motives of perpetrator and mechanism opted for rationalizing the act. To the best of knowledge, this study is pioneering in addressing the issue of partial observability of corporate frauds in the developing economy. It has further research potential to compare the developing and developed economies. Further researches can replicate this idea in another context by applying sophisticated techniques of probability and advanced artificial intelligence methods (i.e., machine learning). Moreover, the role of external auditors in assessing the fraud risk factors can be analyzed in-depth by enhancing the guidance offered by the current study.

6. Main Conclusions and Novel Findings of the Dissertation

This study aims to find the factors that can provide an incentive to the firms for committing manipulation. Overall this study analyzed corporate fraud that can affect the quality of financial reporting. The main objective is achieved through an in-depth analysis of theoretical and empirical literature on corporate misconduct and financial reporting frauds in order to identify prevalent research gaps. This study makes the following novel contributions:

The model of Wang (2004) used in this study generates testable implications for the differences in fraud propensities of the firm. The issue of partial observability of fraud is captured through a system of equation using bivariate probit estimation disentangling the firm's probability to manipulate and the ex-post probability of detection of manipulation. The previous literature on fraud related research either completely ignored the issue of identification/partial observability of fraud or addressed it as a limitation and future research direction. The main novel contribution of this study is to hand collect a sample of firms alleged of financial statement manipulation and fraud by SECP for the first time and apply the techniques bivariate probit model to control the issue of partial detection/unobservability of fraud.

Using partial observability technique to disentangle the unobservable probability of manipulation and the conditional probability of detection of manipulation from the observable probability of detected frauds by SECP, this study found strong evidence for the positive relation between firm’s probability of manipulation and Beneish M-Score indices particularly *sales growth index, days’ sales in receivable index, depreciation index, gross margin index and total accrual to total assets*. The results corroborates to the initial empirical findings presented by Beneish using AAERs database.

The eight indices are based on financial ratios that can either capture the distortion in the financial statements due to manipulation or they indicate firms’ predisposition to engage in earning manipulation and fraud (Beneish et al., 2012). In contrast to the findings of Beneish (1999), this study found a strong support for positive relation between firm’s propensity to manipulate *(M)* and *depreciation index*. Unlike to the initial result, a change from e.g., accelerated to straight-line depreciation or a revision that lengthens assets' useful lives would result in higher values of the depreciation index and considered as incidence of manipulation in the sample of firms alleged of manipulation SECP.

Manipulators tend to overinvest. This study found a strong positive and significant relationship between firm's probability to manipulate and investment intensity. Meanwhile, investment intensity and ex-post return volatility significantly determine the probability of detection of manipulation. Higher investments tend to deceive the investor's since they inhibit the abilities of analysts to predict the future cash flow pattern. Overinvestment by firms with a higher degree of risk or disproportionate relation with existing assets of firms tends to influence the detection of fraud negatively. In contrast to the findings of initial model (Wang, 2013), this study found strong support for positive relation between sales growth and D_i. Higher sales growth, per se, is not negative, but in a rapid increase in sales growth trajectory of firm may alert the regulators and investors and results into detection of manipulation.

SUMMARY

The primary aim of this study is to examine financial reporting fraud, which is one of the significant issues affecting the quality of financial reporting. This study aims to highlight corporate frauds and manipulation in the developing economy setting. This study extends this discussion by highlighting partial observability of frauds. The dissertation comprises of six chapters.

In the introduction section, the background of the study, the rationale of the topic under consideration, the prevalent research gap and contribution has been discussed briefly.

Chapter one explains the research questions, objectives and research approach.

Chapter two provides a comprehensive literature review to comprehend the state of present research related to corporate misconduct in general and financial statement manipulation, in particular. Starting from a general discussion of occupational frauds, more narrowed operational definitions are provided. This chapter also discusses the fraud triangle theory, its development and criticism. Nevertheless, M-Score and other techniques for detecting and deterring manipulation are discussed in details. Finally, hypotheses are deduced based on theoretical and empirical literature.

Chapter three elucidates the materials and methods used for the collection and empirical testing of the data. This chapter also underlines the techniques chosen for identifying firms alleged of misstatements, manipulation and financial reporting frauds. Moreover, a matched sample of control firms is chosen, based on various characteristics. Data collection methods and SIC of manipulators and control firms have been discussed. M-Score analyses and operational definitions of variables are described, including a detail description of sources of data and literature references. This chapter also explains in detailed the empirical methodology and estimation techniques chosen for the analyses of data.

Chapter four describes the research findings and their evaluation. At the beginning of the chapter, a general comparison between control and sample firms is presented. Furthermore, the two samples are compared using univariate analysis. Pairwise correlation, time series analysis of manipulators and cross-sectional analyses are done to compare manipulators and control firms. These analyses found partial support for *hypothesis H1*.

Moreover, a multivariate analysis is executed to compare the indices of M-Score for the manipulators and the control firms. It leads to conclude the results for the proposed *hypothesis H2*. In the second stage of multivariate analysis, the issue of partial observability of fraud is addressed using bivariate probit estimation, disentangling the equation for the

probability of manipulation and the probability of detection of manipulation. The results of these analyses are concluded based on *hypothesis 3 and 4*. In the third stage of multivariate analysis, the robustness of the results is checked. Finally, an evaluation of results based on a simple probit model and bivariate probit model are discussed to affirm the suitability of the chosen model.

Chapter five delineates the conclusion of the study. Conclusions are drawn from the findings of the analyses presented in chapter four. Furthermore, research implications, limitations and future research directions are also presented in this chapter.

Chapter six presents novel findings of the research and conclude the dissertation.

In the end, bibliographic references to the study and annexures are attached.

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11. Asif, K. M., Máté, D., Elyas, A. M., **Sadaf, R.**, Atif, K. M., Popp, J., Oláh, J.: Does Institutional Quality, Innovation and ICT Technologies Promote Financial Development?
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Dedications and Acknowledgements

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I would like to dedicate my thesis to my ***parents***, ***grandparents*** *and my* ***husband.*** *Thanks for believing in me and my work.*

Rabeea Sadaf

DECLARATION

I, undersigned (name: **Rabeea Sadaf**, date of birth: 12/12/1989) declares under penalty of perjury and certify with my signature that the dissertation, I submitted in order to obtain doctoral (PhD) degree is entirely my own work.

Furthermore, I declare the following:

- I examined the Code of the Károly Ihrig Doctoral School of Management and Business Administration and I acknowledge the points laid down in the code as mandatory;
- I handled the technical literature sources used in my dissertation fairly and I conformed to the provisions and stipulations related to the dissertation;
- I indicated the original source of other authors' unpublished thoughts and data in the references section in a complete and correct way in consideration of the prevailing copyright protection rules;
- No dissertation, which is fully or partly identical, to the present dissertation was submitted to any other university or doctoral school for the purpose of obtaining a PhD degree.

Debrecen, 15/03/2020.

Rabeea Sadaf